



Michail Moatsos

# Global Absolute Poverty

Present and Past since 1820

PhD Thesis

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*About the cover:*

*“A linen shirt, for example, is, strictly speaking, not a necessary of life. The Greeks and Romans lived, I suppose, very comfortably though they had no linen.*

*But in the present times, through the greater part of Europe, a creditable day-labourer would be ashamed to appear in public without a linen shirt, the want of which would be supposed to denote that disgraceful degree of poverty which, it is presumed, nobody can well fall into without extreme bad conduct.”*

*Adam Smith (1776, book 5, chapter 2, article 4)*

# **Global Absolute Poverty, Present and Past since 1820**

**Absolute metingen van wereldwijde armoede, vanaf 1820 tot heden**  
(met een samenvatting in het Nederlands)

## **Proefschrift**

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door

**Michail Moatsos**

geboren op 24 oktober 1975  
te Athene, Griekenland

**Promotor:**

Prof. dr. J.L. van Zanden

**Copromotor:**

Dr. A. Rijpma



*To Svetlana-Lito, Nestor Ernesto, Orfeas Martin and  
to my mother for her love and her never-ending sacrifices*

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Στη Σβετλάνα-Λητώ, τον Νέστωρ Ερνέστο, τον Ορφέα Μάρτιν και  
στη μητέρα μου για την αγάπη και τις ατελείωτες θυσίες της

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## Foreword and Acknowledgments

An adventure; a joy; a rejuvenating life-time experience; this is the pragmatological background of this thesis dear reader.

A long time ago in a galaxy far away, right after finishing my studies in physics and automation, and my post-graduate research in biomedical engineering, I found my self deep into business venturing, and any thought of going “back to school” seemed as far as any. Nonetheless, around 2007, as a founder of a TV production company, I pushed the pre-production of an infotainment documentary about money. I was deeply intrigued by John Kenneth Galbraith’s book “Money, whence it came where it went”. The sketch of that documentary seemed to ask some right questions about the negative impact monetization has on societies, but as feedback came piling, it seemed to lack providing any answers. Alas, I had none to offer.

A while later ca. November 2009, the great financial crisis struck Greece, and we had just left the country a couple of months earlier as my dear wife Svetlana, wanted to pursue a PhD track abroad. At the time I was between Germany, where we lived, and France, where I worked. Being able to pull this off was thanks to an online marketing company we started in France with my dear friends Olivier Cotinat, Oliver Bohl, Nicolas Baudran, and Jerome Pelegrin. My wife and I could not have escaped the deep financial crisis in Greece, and pursued our dreams further without their initiative. Olivier was the energy source behind this venture, and for that and his friendship I will always remain in his debt. Angel investor Mathias Monribot believed in us and provided the necessary seed funds to get things started.

However, as I soon realized, marketing is not my cup of tea.

Thereafter, my thoughts were often occupied with the idea to understand better how a monetized society functions. I recalled that back in school, when I had to choose what to study and pass an exam to do so, I lingered extensively between economics and electrical engineering. I chose the later, because in order to be enrolled in a university in Greece to study economics, one needs to take an exam in (how well one can learn) history (by heart). I knew that I did not have the memory for such a task, ergo I opted for beta sciences. But the interest for economics was there to begin with. Same goes for social injustice and material deprivation. Putting all these in scale it was then clear what to do: study economics. At the time, my wife had just started her PhD in Max Planck Institute for Psycholinguistics, so I no more had to be the bread-winner of the family; being a sole bread-consumer can be particularly beneficial at times.

From day one at UU’s Multidisciplinary Economics research master we were asked what interests us the most in economics. My answer constantly was: in-

equality. Fortunately, a few academic periods down the road we had a course taught among others by Prof. Dr. Jan Luiten van Zanden and (the PhD candidate at the time) Selin Dilli, and I had the fortunate assignment of estimating global inequality by replicating the results of Sala-i Martin (2006). The incredible coincidence was that Jan Luiten was the PI of a project on long run global inequalities, and after liking what I did with the assignment, he offered me a student assistantship in his “Clio Infra” project. Moreover, he offered me first author position on an article on global inequality that would end up being published by the OECD. I thought I was dreaming. Jan Luiten was also interested in measuring poverty by applying Bob Allen’s approach on real wages.

For giving me the opportunity to perform this task within a PhD trajectory which resulted to the present thesis, for his guidance, his endless support and the countless events I had the good fortune and resources to partake, I remain in his debt.

*Thank you so much dear Jan Luiten.*

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It goes without saying that path dependency plays a major role in our lives and careers, and the long lasting effect of some people should be acknowledged no matter how long in the past their intervention was. From this angle I wish to thank my former PhD supervisor in Greece Errikos Ventouras, without his excellent letter of recommendation I do not think I would have been accepted at the UU's research master to begin with. The same applies for my former boss at the "Demokritos" National Center for Scientific Research Constantin Makropoulos, and Eleni Zabaka who pushed Constantin in delivering his excellent letter of recommendation before the deadline... I further wish to warmly thank, the director of the English language prep-school I frequented, Mr. Oikonomides for his talent in disciplining the undisciplined with nudges instead of scorn.

A special thanks goes to Daniel Gallardo Albarrán, who I've met by chance at a summer school in Groningen back in 2015 and we slowly evolved to becoming friends, presenting at the same conferences, co-organizing an international workshop at Utrecht University on long run Wellbeing Measurement, and finally becoming co-guest-editors in a special issue of the Journal of Economic Surveys on the same topic. It seems that we perform best at each other's presence. For this and your friendship I thank you Daniel.

My experience of life in Utrecht would have never been as pleasant without the frequent visits to cafe's with Bram van Besouw and Tim van der Valk; the good lads and good friends. At those cafe's we spent hours on (at times "intellectual") small-talk; but not only. Those warm coffees were more often than not an opportunity to exchange and debate ideas, leaving the place one drop wiser each time. For all this I thank you both Tim and Bram. I further wish to thank Tim for kindly translating my English text to a "samenvatting in het Nederlands" and for inviting me to join him and Amaury in becoming the trio of "wealth inequality in the Netherlands"—



side-project which seems to bear fruits and is all bright and promising. Bram, you further have my gratitude for having me as a paranymp (and vice-versa), and for inviting me over to the “Science” paper team. Foremost, I thank you both for your friendship, your honesty and your criticism when I err.

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Lastly, I wish to thank my once upon a time student Lina Papachristou who occasionally visited us from Brussels, as well as Giannis Alexopoulos, Lila Tantalaki and their daughter Evgenia who we’ve met by accident in the little town of Kleve a couple years ago, and it is amazing how many things we share in common.

It is evident from the above lengthy list of people of which I feel the need to acknowledge their positive presence throughout our life changing adventures in Western/North-Western Europe, that I have been unthinkably fortunate. Time after time, at all critical –or less so– moments there was someone to support me or help me out, and step by step I felt all the richer.

*I promise that I will carry on this utmost beneficial tradition and be of help to*

*others to the best of my abilities.*

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– *And what does Greece have that you like so much?*

– *Light and poverty.*

HENRY MILLER

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## Samenvatting in het Nederlands

Het ontsnappen aan armoede, en met name de conditie van extreme ontbering, wordt gezien als het onderliggende doel van wereldwijde economische groei. De ontwikkelingsdoelen van de Verenigde Naties, waaronder de millenniumdoelstellingen (MDG1) en zijn opvolger, de duurzame ontwikkelingsdoelen 1.1, richten zich op de vermindering van absolute armoede. De literatuur over het meten van armoede loopt echter achter en wordt gedomineerd door publicaties met officiële statistieken van de onderzoeksgroep van de Wereldbank om de eerdergenoemde doelen te behalen. Verder bestaat de academische literatuur uit slechts een gepubliceerd artikel (Bourguignon and Morrisson, 2002), terwijl een aanzienlijke hoeveelheid data sindsdien beschikbaar is gekomen. Belangrijker nog is dat de literatuur bouwt op een methodologie die al 20 jaar hevig bekritiseerd wordt.

Het concept van armoede wat ik mijn thesis gebruik is er een van objectieve absolute armoede. Objectief, omdat armoede wordt bepaald aan de hand van objectieve maatstaven en niet op basis van zelf gerapporteerde gegevens. Absoluut, omdat a) de relatieve positie van het individu geen invloed heeft op mijn maatstaf van armoede en b) de maatstaf van welzijn die is gevat in de armoedelijnen vaststaat in absolute termen. Deze keuzes zijn gemaakt om ervoor te zorgen dat de toegepaste methodiek enerzijds tegemoetkomt aan de kritieken binnen de literatuur op de huidige standaard, en anderzijds om een vergelijking met diezelfde standaard mogelijk te maken door het gebruik van eenzelfde armoedeconcept. Door eenzelfde armoedeconcept te gebruiken wordt het mogelijk om het effect van één enkele armoedelijijn op zowel het niveau als de trend van armoede te identificeren.

Het onderliggende idee van de evaluatie van armoede in deze thesis is niet om een specifiek niveau van welvaart te verdedigen doormiddel van een armoedelijijn. In plaats daarvan wordt er een nieuwe maatstaf van armoede geïntroduceerd die welvaart op zodanige wijze meet dat deze (absoluut) te vergelijken is door ruimte en tijd. Elk hoofdstuk introduceert een armoedelijijn met een zekere levensstandaard die vervolgens systematisch wordt toegepast.

Hoofdstuk 2 geeft een compleet overzicht van de huidige staat van de literatuur, inclusief de verschillende methodologische keuzes die daarbinnen gemaakt (kunnen) worden. Het doel van dit hoofdstuk is om de verschillende methodieken om niveaus en trends van wereldwijde armoede vast te stellen kritisch te evalueren. Daarbij kan er onderscheid gemaakt worden tussen welvaardsdistributies (inkomen en consumptie), de exacte armoedelijijn, gemiddeld inkomen en consumptie per distributie, en de toerekening voor missende landen en data.

Hoofdstuk 3 neemt een volgende stap en past een kosten-van-basisbehoefte-methodiek toe op wereldwijde schaal. De analyse integreert alle ontwikkelende landen van 1985 tot 2014. De exacte armoedelijijn wordt bepaald aan de hand van

een literatuur over historische reële inkomensreeksen en een consumptiepakket op bestaansminimum (Allen, 2001; Allen et al., 2011; de Zwart et al., 2014).

Deze exercitie leidt tot vier conclusies. Een, globale armoede op basis van het bestaansminimum ligt substantieel lager dan armoede op basis van de dollar per dag methodiek. Twee, de geografische distributie van armoede verschilt aanzienlijk ten opzichte van de dollar per dag methodiek, zowel in rangschikking als in absolute bijdrage. Drie, de vermindering van armoede ten opzichte van het referentiejaar van de eerste milleniumdoelstelling (MDG1) is veel lager dan het doel van 50 procent. En vier, de waarde van de armoedelij n op basis van het bestaansminimum verschilt sterk van de 1.9 dollar per dag voor bijna elk land en jaar. Deze laatste conclusie toont aan dat de dollar per dag methodiek voorziet in een consumptiepakket met verschillende welvaartsstandaarden door tijd en ruimte, wat ingaat tegen onderliggende fundamentele aannames binnen deze methodiek.

Hoofdstuk 4 gaat in op de snelle afname van wereldwijde armoede die de dollar per dag methodiek identificeert. In dit hoofdstuk onderzoeken we de onderliggende methodiek en herbouwen we deze met Monte-Carlo microsimulaties. We laten zien dat MDG1 niet behaald wordt met een betrouwbaarheidsinterval van 95 procent, maar slechts met 77 procent.

Hoofdstuk 5 maakt een pas op de plaats en introduceert de benodigde data om armoede te meten op basis van inkomensdistributies. Dit hoofdstuk bouwt op het werk van Zanden van et al. (2013). Met behulp van de data berekenen we de evolutie van wereldwijde inkomensongelijkheid.

Hoofdstuk refsec:GP richt zich wederom op maatstaven van wereldwijde armoede en biedt een eerste toepassing van de kosten-van-basisbehoef ten methodiek op een wereldwijde schaal en over de periode 1820-2018. Het meeste in het oog springende resultaat van deze exercitie hangt samen met het totale aantal mensen dat in extreme absolute armoede verkeerd wereldwijd. Mijn bevindingen laten zien dat dit aantal 757 miljoen was in 1820 en 764 miljoen in 2018, ondanks de sterke afname van het percentage van de wereldbevolking dat in armoede leeft. Dit percentage was gelijk aan 76 procent in 1820, 60 procent tegen het einde van de 19e eeuw en 25.5 procent rond 2000. Tegen 2018 bedraagt het CBN globale armoede-cijfer 10%.

Het doel van deze thesis is om a) een alternatieve methodiek te introduceren om wereldwijde armoede te meten op basis van de kosten van basisbehoef ten en b) deze methodiek empirisch en methodologisch te operationaliseren, zowel voor vandaag als op de lange termijn. Deze methodiek wordt vervolgens vergeleken met de standaard dollar per dag methodiek om de beperkingen van deze standaard te onderzoeken. Daarnaast worden ook de beperkingen van de kosten-van-basisbehoef ten methodiek geïdentificeerd, en waar mogelijk verbeteringen voorgesteld en empirisch onderzocht.

De methodologische innovatie binnen mijn thesis heeft mogelijk ook toepassingen buiten het vakgebied over maatstaven van armoede. Zo is het bijvoorbeeld mogelijk om mijn methodiek toe te passen in onderzoek naar (historische) reëel inkomen. Net als bij onderzoek naar armoede staat de vergelijking van inkomen met een zekere standaard centraal in onderzoek naar reëel inkomen, en de kosten van basisbehoeften methodiek voorziet hierin. Dit zou een mooi voorbeeld zijn van indirecte kruisbestuiving tussen verschillende onderzoeksvelden, zeker ook omdat mijn werk geïnspireerd is op het werk van Bob Allen over reëel inkomen.

## List of Abbreviations

<b>CPIAP</b> .....	Consumer Price Index for the Absolute Poor
<b>CR</b> .....	Chen and Ravallion (2010, 2009)
<b>DD</b> .....	Deaton and Dupriez (2009)
<b>EA</b> .....	East Asia
<b>EECA</b> .....	Eastern Europe and Central Africa
<b>EEfSU</b> .....	Eastern Europe and former Soviet Union
<b>GDP</b> .....	Gross Domestic Product
<b>HHS</b> .....	Household Survey
<b>iPL</b> .....	International Poverty Line
<b>LAC</b> .....	Latin America and the Caribbean
<b>LCU</b> .....	Local Currency Units
<b>MDER</b> .....	Minimum Dietary Energy Requirement
<b>MDG1</b> .....	The first Millennium Development Goal
<b>MENA</b> .....	Middle East and North Africa
<b>NAS or SNA</b> .....	National Account Statistics or System of National Accounts
<b>NIPA</b> .....	National Income and Product Accounts
<b>PFCE</b> .....	Private Final Consumption Expenditure
<b>PPP</b> .....	Purchasing Power Parity
<b>RCS</b> .....	Ravallion et al. (2009)
<b>RDV</b> .....	Ravallion et al. (1991a), or Ravallion et al. (1991b)
<b>SA</b> .....	South Asia
<b>SSA</b> .....	Sub-Saharan Africa
<b>SSEA</b> .....	South and South East Asia
<b>P4s</b> .....	Purchasing Power Parities for the poor
<b>PWT</b> .....	Penn World Tables
<b>WBGC</b> .....	World Bank Global Consumption Database



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# Chapter 1

## Introduction

by Michail Moatsos

Escaping poverty, and especially living conditions that are characterized by some form of extreme deprivation, is considered to be the prime objective of economic development across the globe. The United Nation's flagship development goals, either as the first Millennium Development Goal or, its follow-up, Sustainable Development Goal 1.1, underlie this perspective and focus on the topic of extreme absolute poverty reduction.<sup>1</sup> Yet the literature on poverty estimation on a global scale is relatively small, and primarily populated by official statistical results by scholars at the World Bank Research Group, which acts as a scorekeeper to the aforementioned UN goals. Moreover, the literature on long run poverty estimations consists of only one published article (Bourguignon and Morrisson, 2002), while a substantial volume of new data has become available since. Most importantly, the entire body of global poverty literature rests on a methodology that has been extensively criticized for the last 20 years.<sup>2</sup> Recent calls for change challenge this conformity and have found way into the most official critique against the dollar-a-day official standard, albeit elegantly subtle, in the report of the World Bank's Commission on Global Poverty, presided by the late Sir Tony Atkinson (Atkinson, 2016).

Current official estimates of global poverty show that it contracts tremendously since the turn of the millennium. Yet hunger, an indicator closely linked to poverty,

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<sup>1</sup>MDG1: "Target 1.A: Halve, between 1990 and 2015, the proportion of people whose income is less than \$1.25 a day" from <http://www.un.org/millenniumgoals/poverty.shtml>, accessed on March 14, 2017; SDG Target 1.1: "By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than \$1.25 a day" from <https://sustainabledevelopment.un.org/sdg1>, accessed on March 14, 2017.

<sup>2</sup>With the notable recent exception of Allen (2017).

and especially to extreme poverty, demonstrates a much slower reduction.<sup>3</sup> In addition, recent counts of the number of undernourished people are higher than the number of people reported as living in conditions of extreme poverty.<sup>4</sup> Although this is not an a priori contradiction, it is certainly a puzzling result. Being able to avoid undernourishment is a core property of poverty lines around the world,<sup>5</sup> and a core component in Amartya Sen's capabilities approach.<sup>6</sup> Hence, there is good reason to suspect that these estimates may stand in need for improvement, as those being undernourished should most likely be less than those living in a condition of poverty.<sup>7</sup> Problems may well lie on both sides, but given the extensive debate regarding the standard definition of global poverty using the dollar-a-day method, the first focus of an investigation would be the definition and use of the 1.9\$/day poverty line in all countries for all years to estimate poverty levels and trends for the world as a whole.

Given that at the present all research on global poverty,<sup>8</sup> contemporarily or historically, is being conducted by applying one poverty line, the implications, if this approach is potentially biased, or even erroneous, may very well be of substantial importance for the evolution of poverty both for the most recent years as well as for those of the more distant past.<sup>9</sup> Unless we put forward a framework for global poverty measurement that circumvents the fundamental problems of the standard method, we will not be able to identify how much our appreciation of global poverty in the past has been possibly biased.

Methodological issues aside, on a micro level the important issue is the development of human capacity to circumvent unfavorable – and exploit favorable – life circumstances in order to achieve higher levels of welfare, ergo escaping poverty. While on a macro level, “[t]here is, perhaps, no better test of the progress of the nation than that which shows what proportion are in poverty, and for watching the

---

<sup>3</sup>The United Nations Food and Agriculture Organization (FAO) estimates a reduction of about 21% in the period 1990-2015, while the World Bank estimates the reduction of poverty to be at about 72% in the same period.

<sup>4</sup>FAO estimates that in 2015 795 million people were undernourished, while the World Bank reports that in 2015 736 million people were living in conditions of absolute extreme poverty as defined by the 1.9\$/day standard.

<sup>5</sup>See Ravallion et al. (2008, Table A1).

<sup>6</sup>See Sen (1983, p.162).

<sup>7</sup>Even if some individuals willingly forego some important nutrients to consume other items, it is hardly convincing that those people – being forced to make those choices – are in all likelihood not poor.

<sup>8</sup>On absolute global poverty to be exact, and at the time of writing of this text (January 12th, 2020); see below for an explanation of the distinction between absolute and other forms of poverty, and further details. See also table 2.1 for the full list of relevant articles.

<sup>9</sup>At times the literature uses more than one dollarized international poverty line for the purpose. Any possible biases would be relevant to each of these lines separately as well.

progress the exact standard selected as critical is not of great importance, if it is kept rigidly unchanged from time to time.” (Bowley, 1915).<sup>10</sup> There are two important points to be taken from this quote: (a) the use of poverty as a measure of overall prosperity in a country, and (b) the need for the standard of measurement to be “rigidly unchanged” for practically as long as we want to compare.<sup>11</sup> The former gives the topic of poverty an additional motivation for research, besides the moral obligation against those living in poverty vis-a-vis those living in affluence; while the later is recognized as the sine qua non in poverty measurement (Ravallion, 2016b, p.5).

At the core of poverty measurement lies the poverty line. There are competing methods to estimate a proper poverty line, and scholars or national authorities,<sup>12</sup> typically utilize what is called a “cost of basic needs” (CBN) approach to define national poverty lines.<sup>13</sup> The method consists of drawing a budget that would just suffice for some bare necessities in life, such as food and water, shelter, sanitation, transport, etc. As alluded above, on a global scale a different route is taken using a statistical approach dubbed the “dollar-a-day” (hereafter also DAD) method, which is adopted by the World Bank and the United Nations for tracking the evolution of global poverty.

Regardless of the way one defines the poverty line, there are a few more basic ingredients in measuring poverty from the perspective of a poverty rate.<sup>14</sup> Besides the poverty line, the other main ingredient is the distribution of income or consumption across individuals or households. With those two ingredients at hand one can identify the poverty rate by locating on the distribution the share of people that have income or consumption below the level specified by the poverty line. For producing estimates on a global scale, beyond the availability of poverty lines and distributions for each country, one further needs information on each country’s population size. Then to calculate the global poverty rate one simply needs to take

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<sup>10</sup>Quotation from p.213, cited in Sen (1979). The implied poverty definition here is that of an absolute one. The two rather competing concepts of poverty, absolute and relative, are discussed further below.

<sup>11</sup>This extension in time compared to the way Bowley frames it may not follow directly from his statement, but such an extension makes sense in a first attempt to measure poverty with the same standard across large time intervals. Further work would be necessary to provide the theoretical foundation of how a standard should change “from time to time” and how frequent those changes should be.

<sup>12</sup>In developing economies national authorities are occasionally assisted by the World Bank as well.

<sup>13</sup>(Chen and Ravallion, 2010) report that about 80% of the NPLs in their sample is using a version of the CBN method. Developed countries typically use relative poverty lines, see below for details.

<sup>14</sup>The main statistic used throughout this thesis is the poverty rate which is the percentage of people having a consumption expenditure or income below the poverty line. There are many other indicators to measure poverty with. For a discussion of those indicators see Ravallion (2016a).

the average poverty rate across countries weighted by their respective population.

The delineation of the global poverty measurement debate, the scrutinization of the dollar-a-day methodology, and the empirical implementation of the cost of basic needs approach over the long and the short run are the core substances of this thesis. Without a doubt, this thesis is not about addressing all problems related to global poverty measurement. Rather, this thesis aims at answering three main research questions: (a) identify the level and the evolution of global poverty (across all countries) over the long run since 1820 using the cost of basic needs approach; (b) estimate the uncertainty of the standard method and compare it with the uncertainty of the proposed cost of basic needs alternative; and (c) identify possible differences between the standard method and cost of basic needs implementations for the recent, more data abundant, period among developing countries.

## **1.1. Poverty concepts in brief**

As early as 1902 Rowntree proposed the distinction between primary and secondary poverty. Primary being the lack of sufficient income or, equivalently, access to adequate resources; and secondary poverty, being the result of mismanagement by the household, or the individual, of adequate income or resources that would otherwise provide for a living standard outside of poverty. In the latter case, lack of economic means is not the source that causes the poverty conditions, but their mismanagement. Similarly, Townsend (1979) saw poverty as an economically enforced deprivation. He distinguished between measuring direct, or resource, poverty (by measuring available economic resources), and indirect poverty, or material, deprivation (by measuring living standards). Then he would identify as the “truly” poor those cases where the former explained the latter. Therefore the truly poor would be those living in conditions of material deprivation where this deprivation is a result of lack of resources, and, as in Rowntree, not the mismanagement of those resources.

The gap between the two characterizations of poverty, as primary/secondary according to Rowntree and direct/indirect poverty according to Townsend, is described better by Amartya Sen who puts forward the possible differences in the “respective abilities [of individuals] to convert commodities into capabilities” (Sen, 1983, p.165). Such an expansion entails that with the same access to resources, different individuals may be variably characterized as living in poverty or not, depending on their particular ability to convert the various commodities at their disposal to elements that enter directly to their utility.

Within a welfare system, a poverty definition may also be the result of political or administrative processes, when for example a particular threshold is chosen to distinguish those entitled to some sort of social assistance. Not entirely unre-

lated to this is the concept of income poverty. This can take the form of relative income (a percentage of mean or median income), or subjective income, meaning the amount of income someone thinks is necessary to make (his or her own necessary) ends meet. The concept of subjective income can be contrasted with that of objective income, which is a monetary amount that allows one to acquire a particular –commonly accepted– set of goods and services. More generally, subjective poverty is based on the individual’s perception of own poverty, while objective poverty is based on measurable dimensions of wellbeing.<sup>15</sup>

On these concepts one can add the measurement of material deprivation and social exclusion which are part of the definition of poverty used by Townsend (1979, p.31): “Individuals, families and groups in the population can be said to be in poverty when they lack the resources to obtain the types of diets, participate in the activities and have the living conditions and amenities which are customary, or at least widely encouraged or approved, in the societies to which they belong. Their resources are so seriously below the average individual or family that they are, in effect, excluded from ordinary living patterns, customs and activities.”

Sen offers the more all-encompassing capabilities framework which can trace poverty at higher and lower levels of living standards, for example the widely referred to subsistence level: “the poverty line may be defined to represent the level at which a person can not only meet nutritional requirements, etc.” (Sen, 1983).<sup>16</sup> Sen (1983) further emphasizes that: “absoluteness of needs is not the same thing as their fixity over time”, and that “[e]ven under an absolutist approach, the poverty line will be a function of some variables, and there is no a priori reason why these variables might not change over time.” This point reinvigorates the rationale of Bowley from early 20th century.

## 1.2. In pursuance of global poverty

The long tradition of measuring poverty on a local and national level dwarfs the recent approaches to measure poverty on a global scale. The exercise from a global perspective is a relatively new possibility. Only since the early 1990s data exist that allow the estimation of poverty on a reasonably global scale. Along with the capacity to measure poverty globally came an increasing interest on the topic of

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<sup>15</sup>As discussed below, this thesis does not consider subjective approaches to poverty measurement. Official measures of poverty typically relate to objective poverty, which may be linked to some entitlements or social welfare benefits.

<sup>16</sup>Amartya Sen’s capabilities approach can be thought of as a multidimensional measure of poverty. This thesis does not expand on multi-dimensional considerations of poverty. For more information on multidimensional global approaches see Alkire and Santos (2014); Alkire et al. (2013); Alkire and Foster (2011).

global poverty. In any case though, poverty conditions are better understood within their own context, and therefore much more on a local level rather than a global one.

However, even on a local level, there is hardly a consensus around the world regarding how poverty should be measured, with one tradition focusing on some – typically frugal – poverty lines, a method pioneered by the work of Rowntree (1901) and Booth (1904). Yet another, newer, tradition pioneered by Fuchs (1967)<sup>17</sup> held the view that in developed countries those poverty lines that largely correspond to levels of subsistence are totally irrelevant, and poverty should be seen only in its relative form, which largely corresponds to the general concept of income inequality.

This dichotomy in poverty research largely survives to this day. Most<sup>18</sup> developed countries follow a relative poverty definition,<sup>19</sup> while in developing countries it is a frugal (or less frugal) poverty line – kept constant in real terms throughout the years – that is being used to measure national poverty. This second approach is dubbed absolute poverty, since its goal is to estimate the number or share of people who live below an absolute welfare level. This is in contrast to the strictly relative poverty notion which dictates that only the relative position of an individual, vis-à-vis all others, is what counts for one's own welfare, regardless of the absolute level of welfare she or he is able to achieve.<sup>20</sup>

### 1.3. The need for an alternative approach

Since its inception in the 1990s the dollar-a-day (DAD) approach dominates the domain of global poverty research. Every absolute global poverty estimate is relying on this method.<sup>21</sup> Despite its simplicity and its merits, the method has been under the lens of important critics. Over the years this list of scholars only grows.<sup>22</sup> There is one core methodological choice, and three key problems linked explicitly

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<sup>17</sup>Although the point has been recognized already, for example by Galbraith (1958) who argued that “[p]eople are poverty stricken when their income, even if adequate for survival, falls markedly behind that of their community.”

<sup>18</sup>USA being a notable exception.

<sup>19</sup>Typically the share of population having less than 60% of the median or 50% of the mean income of all households.

<sup>20</sup>See Ravallion and Chen (2017) for a further discussion of these distinctions.

<sup>21</sup>Ravallion et al. (1991a); Chen et al. (1994); Ravallion and Chen (1997); Chen and Ravallion (2001); Bourguignon and Morrisson (2002); Bhalla (2002a); Chen and Ravallion (2004); Sala-i Martin (2006); Pinkovskiy and Sala-i Martin (2009); Chen and Ravallion (2010); Zanden van et al. (2011); Pinkovskiy and Sala-i Martin (2016).

<sup>22</sup>Deaton (2001); Srinivasan (2009); Reddy and Pogge (2010); Deaton and Dupriez (2011a); Subramanian (2015); Atkinson (2016); Allen (2017).

with the dollar-a-day method. Those key problems are largely the direct result of that core methodological choice. I will first refer to the key problems and then the core choice.

The key problems are: (a) the application of Purchasing Power Parity (PPP) exchange rates<sup>23</sup> used to convert local currencies to a common currency (international PPP dollars); (b) the use of an average consumer price index (CPI) that does not track the price changes relevant to those living in conditions of poverty; and (c) the underlying method of derivation of the—nowadays— 1.9\$/day international poverty line.<sup>24</sup>

At the core, PPP and CPI encompass essentially the same methodological problem, as they are both built around the expense patterns of the average household, not the households living in conditions of poverty.<sup>25</sup> The highly likely divergence between the price index of the average household and a household living in poverty can influence decisively the poverty estimates, contemporary and historically.<sup>26</sup>

On the other hand, the method of derivation of the 1.9\$/day which boils down to taking an average of 15 national poverty lines.<sup>27</sup> This in turn instills a vague meaning in terms of which level of living standards that the 1.9\$/day allows for in a particular country, as there is no such thing as an average country, and introduces large uncertainty regarding the value of the poverty line.<sup>28</sup> At the same time the 15 national poverty lines, that are being averaged, lack methodological coherence in their definitions. This makes them only nominally comparable, not by composition or meaning, and therefore taking their average can be viewed as a methodologically questionable choice.<sup>29</sup>

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<sup>23</sup>Purchasing Power Parity (PPP) exchange rates are different from the market rates since they account for the additional purchasing power than currencies of less economically developed countries have in their respective markets because of the relative cheaper non-tradeable goods or services.

<sup>24</sup>Other problems, such as data imputations, pertain the final figures on global poverty, but not the dollar-a-day method per se.

<sup>25</sup>For a detailed exposition of additional issues with PPP and CPI use see chapter 2.

<sup>26</sup>The term of inflation inequality to describe this effect in poverty is very relevant here. See the work of Wimer et al. (2019) for the USA, where they find that considering those differences in price changes increases the total number of people living in poverty by 3.2 million for 2018, or 8% larger than the official measure. Recent attempts to create PPP exchange rates for the poor by Deaton and Dupriez (2011a) had limited access to the necessary empirical data, and therefore, as the authors openly recognize, their PPP's do not address the problem extensively.

<sup>27</sup>The articles defining this poverty line (Ravallion et al., 2009; Ferreira et al., 2016) offer an empirical framework for the estimation of its value which is the average of the National Poverty Lines of the 15 poorest countries in terms of private consumption per capita in their dataset. Chapters 2 and 4 discuss the definition at length.

<sup>28</sup>Although this uncertainty is not officially reported, it can be calculated nonetheless, see chapter 4 for a first estimation. The source of this uncertainty is that the values of those 15 national poverty lines vary considerably, thus their average is not a good and representative model for them.

<sup>29</sup>Ravallion and Chen (2017, p.22) –respectively former and current World Bank researcher–

As mentioned above, behind the three key problems mentioned above, lies the core methodological choice in the dollar-a-day approach. This core choice is the axiom that one international poverty lines can represent the same type of welfare, or allows for the same level of living standard, throughout the globe and in all of the years. This is arguably a very strong assumption and its validity has not been investigated in the literature. It is simply being taken for granted. I argue that investigating this assumption is a sine qua non element in the domain of global poverty research, and I implement an alternative approach in following the CBN method.<sup>30</sup>

The vehicle for such an investigation is the common method of setting absolute national poverty lines throughout the world: the cost of basic needs approach. Proposals to measure global poverty using a well defined fixed consumption basket has been rejected by World Bank officials based on the reasonable argument that the poor will adapt their consumption habits as a result of price changes (Ravallion, 2010a). Allen (2013), argues that despite the validity of the point, this type of behavior can be accommodated by calculating an adaptive and country specific yearly re-estimated consumption basket.<sup>31</sup>

In 2016 the World Bank's Commission on Global Poverty, presided by the late Sir Tony Atkinson, published its extensive report on Monitoring Global Poverty (Atkinson, 2016). The report argues for the implementation of 21 focused recommendations. Among those that the World Bank has decided not to implement in the foreseeable future, or not at all, are recommendation 5 on estimating the errors of its global poverty estimates, and recommendation 15 on using the cost of basic needs as a supplementary global poverty indicator to be reported together with the dollar-a-day flagship estimates. In light of these developments, and ahead of the 2030 Sustainable Development Goal deadline, it is important that research

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recognize this problem stating that: “[i]n using data on national poverty lines to calibrate welfare-consistent international lines one requires a strong identifying assumption, namely that the national lines represent the local costs of a common global level of welfare needed to not be considered poor [...]”.

<sup>30</sup>For a rare exception see the Asian Development Bank poverty line, Asian Development Bank (2014). In their analysis they argue that the at the time dollar-a-day standard poverty line was not relevant in the Asian context: “\$1.25 a day is not enough to maintain minimum welfare in many parts of our region. A fuller understanding of poverty is needed to help policymakers develop effective approaches to address this daunting challenge.” - Shang-Jin Wei, ADB Chief Economist; see more at <https://www.adb.org/features/redefining-poverty-asia-and-pacific-adbs-take>, last visited on December 12th, 2019. This official view of the Asian Development Bank indicates that the core methodological choice behind the dollar-a-day approach is sub-optimal for a global application.

<sup>31</sup>One way of dealing with this is through linear programming. See Moatsos (2017a) and Allen (2017) for some examples. Linear programming is used in all poverty related empirical chapters of this thesis.



on measuring global poverty addresses these shortcomings in both theoretical, but mostly in an empirical manner.<sup>32</sup> From the perspective of this thesis it is an opportunity to bridge a solution on a present day methodological problem, to the long run historical appreciation of poverty on a global scale.

## 1.4. Global scale cost of basic needs applications

The concept of poverty I use throughout my thesis is that of objective absolute poverty. Objective because it is based on the appreciation of poverty based on estimated objective measures, and not on self-evaluation by individuals. And, absolute because (a) the relative position of the individual among all others has no impact on the poverty measures used here, and (b) the wellbeing standard encapsulated in the poverty lines is held fixed in absolute terms. These choices are made given that the main glossing of this thesis is to use a methodology that attempts to address the concerns raised in the literature regarding the current standard, but still be comparable with that standard by using the same underlying poverty concept. Keeping the same concept will allow the identification of the effect that a single international poverty line has in the appreciation of the levels and trends of global poverty.<sup>33</sup>

The general idea behind the poverty evaluations in this thesis is not to defend any specific welfare level, represented by the applied CBN poverty line,<sup>34</sup> as the proper for global poverty measurement. Instead, the idea is to provide global poverty estimates that represent comparable (absolute) welfare levels across the globe with a method that can be consistently applied across countries and years. Each chapter considers a poverty line that targets different living standards, and the goal in each of them is to apply that poverty line systematically and consistently across time, and across countries.

The first step into delving the field of global poverty is through a detailed commented overview of the literature. Chapter 2 provides such an overview regarding the state of the art in the literature. The complete set of articles on global absolute poverty estimates is covered in considerable length, and the various finer methodological choices in each article are compared and commented. The critical views of

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<sup>32</sup>Kindly the report has positively referred to my research conducted within the framework of this thesis (specifically for chapter 3).

<sup>33</sup>There are various aspects of poverty measurement which are not dealt with in this thesis, for example the issue of chronically poor; see Chaudhuri and Ravallion (1994) for an exposition; in addition the available data do not allow to see within a household for possible misallocation of resources, so we cannot differentiate living standards per household member in terms of gender, age, etc.

<sup>34</sup>Chapter 3 uses also the term “subsistence basket” or “bare bones basket” (BBB), which are both very frugal versions of the CBN approach, in line with the tradition of Allen (2001); Allen et al. (2011).

other scholars in the field are discussed in context as well. The goal of the chapter is to provide the reader with a deep exposition of the competing applications in appreciating the levels and trends of global poverty. Some major distinctions include the choice of welfare distributions (between income and consumption), the exact poverty line(s), the average income or consumption assigned to each distribution, and the imputation methods for missing countries and data.<sup>35</sup>

Chapter 3 takes the first step in applying a cost of basic needs poverty line on a global scale. The analysis includes all developing countries<sup>36</sup> for the years 1985-2014. The exact poverty line definition draws heavily on the historical real wages literature by using the subsistence consumption basket (Allen, 2001; Allen et al., 2011; de Zwart et al., 2014). A number of innovations are introduced, most importantly the objective estimation of the energy required for heating one's lodging space.<sup>37</sup> The price data used here are the post-1984 consumption prices from the October Inquiry conducted by the International Labor Organization (ILO), supplemented by prices from the United Nations (UN) World Food Program (WFP), and UN's Food and Agriculture Organization (FAO).

The ILO October Inquiry is the main data source that makes the long run and short run poverty calculations in this thesis possible (in all the poverty related empirical chapters, namely 3, 4 and 6). This large statistical exercise conducted uninterruptedly from 1925 until 2008 includes data on basic commodity prices, wages, and working hours of wage laborers. The purpose of collecting these data, from the ILO perspective, was to appreciate the evolution of living conditions for the working class. As such, it makes for an excellent source of commodity prices paid by those who one would expect to achieve a living standard not too far from that of a poverty line. At its peak, during the 1960s, it covered about 130 countries, and contained more than 40 basic consumption items, covering staple food items, meat, vegetables, fruits, fish, milk, fuel products, as well as condiments. This source allows the estimation of the cost of a basic consumption basket uninterruptedly for more than 80 years for several developed countries, and for many years within the period for a large group of currently developed and developing countries.<sup>38</sup>

The living standard targeted by the poverty line definition used in chapter 3 is particularly low, and almost traces the level of physical survival.<sup>39</sup> The consump-

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<sup>35</sup>In many occasions the available distributions come with an average value from the conducted Household Survey, but in many other cases this information is missing. Authors differ in how they fill in the missing information, and some decide to substitute the available average values with others according to their preferences (e.g. with GDP per capita).

<sup>36</sup>For comparison with the World Bank results I use the same definition in categorizing a country as developing which is done using its status according to the 2005 World Development Indices.

<sup>37</sup>The method used here has later been used by Allen (2017), as kindly recognized by the author.

<sup>38</sup>Chapter 6 discusses the pros and cons of this source at length.

<sup>39</sup>Naturally the lower the level of living standard one is focusing at, in defining poverty, the less

tion basket provides for the appropriate average amount of kilocalories (kcal) for the population according to the FAO standards, and linear programming is utilized to estimate the cheapest combination of products to achieve this. The exact number of kcal is estimated separately in every year and country based on the demographic profile of the population and anthropometric data (height).<sup>40</sup> This makes the poverty estimates relevant to the population in developing countries “as it is” in every year, and not with reference to a particular population at some arbitrary benchmark year.<sup>41</sup> In addition, the food component of the consumption basket includes fixed amounts of meat, beans and sugar; and the non-food component expenses on heating, clothing and a frugal allowance for housing.

To maximize comparability with the official dollar-a-day results, in all other aspects of global poverty calculations, I use the same exact sources for HHS and population data as the World Bank does.<sup>42</sup>

There are four main conclusions one can draw from this exercise. First, the global poverty rates for subsistence are substantially lower than the dollar-a-day global poverty rates. Second, the geographical distribution of the people living in subsistence poverty is considerably different –both in terms of rankings of regions and their absolute contributions– than the one according to the dollar-a-day approach. Third, the reduction of the poverty rate between the benchmark years of the first Millennium Development Goal (MDG1) is much less than its 50% target. And fourth, the value of the subsistence poverty line is very different from the 1.9\$/day almost for every country and year. This last finding implies that in all likelihood the dollar-a-day allowance would purchase a consumption basket that would provide for a varying level of living standards depending on the country and year. This runs against the basic assumption behind the dollar-a-day standard.<sup>43</sup>

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the (absolute and relative) difference would be between those in direct and those in indirect poverty, simply because of the less room available for the mismanagement of resources to bring one below the poverty line. Put differently, the more the level of the living standard is closer to a bare minimum the less important in identifying the number of those in poverty is any type of less than extreme mismanagement.

<sup>40</sup>This approach addresses the concerns about the kcal content of the subsistence basket in Allen (2001); Allen et al. (2011) by Humphries (2011).

<sup>41</sup>In a personal correspondence Martin Ravallion disagrees with this point, and characterizes this approach as relative (Ravallion, 2016b). I think there are valid arguments against his particular view. For example, one can turn this argument on its head: fixing the kcal target at some point in time makes the poverty estimates relative to that specific point in time, while when the kcal target is estimated on a year by year basis for every country, the resulting poverty estimates are relevant to the population for which all other the economic data that enter the poverty calculations refer to as well.

<sup>42</sup>Using the available distributional information at the World Bank’s PovcalNet platform.

<sup>43</sup>More recently Hirvonen et al. (2019) and Alemu et al. (2019) have shown similar results by evaluating the cost of a nutritious diet around the world using the 2011 ICP price data. Chapter 6 corroborates this conclusion by using a different and less frugal CBN definition.

Chapter 4 has as its direct focus the issue of the relatively recent fast-reducing trends in global poverty, identified by the dollar-a-day method. As such, the main element missing from the official global poverty estimates is an appreciation of their error term (Atkinson, 2016). This is a major point criticized by the Commission on Global Poverty, and it is one of the two “glosses” of its report.<sup>44</sup> It is crucial to have an appreciation of the confidence interval behind the official estimates in order to identify the level of certainty that a specific poverty reduction took place.

In this chapter we scrutinize the dollar-a-day approach and we re-build it on a Monte Carlo micro-simulation setup.<sup>45</sup> This allows us to account for various sources of error, among which are the uncertainty in the PPP exchange rates, and most importantly the averaging step in the dollar-a-day identification, where the average of 15 NPLs of low-consumption developing countries is taken to estimate its \$1.9-dollar value per day. Overall we account for more than half of the error sources mentioned in recommendation 5 regarding the “total error” approach in the report of the Commission on Global Poverty.<sup>46</sup> We demonstrate that the averaging step, in the estimation of the exact value of the \$1.9/day line, is the source of most of the uncertainty in the dollar-a-day estimates, and the reason why MDG1 fails to obtain at a 95% confidence level. We identify that MDG1 appears to obtain at a 77% confidence level.

Interestingly the estimation of global poverty for 1990 using the reconstructed dollar-a-day approach has mean of 39.5% and a rather too broad 95% confidence interval at 11.5%-66%, and in 2015 a mean of 11.9% with a similarly broad confidence interval from 2.1% up to 29.8%. The confidence interval of the dollar-a-day values is 0.91 to 3.23\$/day with an average at exactly 1.9\$/day. Although the mean value is identical to the official international poverty line, the surrounding confidence interval is substantial. These highly uncertain estimates echo the voiced concerns of an advisory board member in the Commission on Global Poverty: “the margin of uncertainty for the global poverty estimates is so large that there must be serious questions about whether they are worth doing in anything like their current form”, (Atkinson, 2016, p.54).

In comparison, the CBN approach demonstrates a much sharper estimation of global poverty in both MDG1 benchmark years. For 1990 it identifies a poverty

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<sup>44</sup>According to the American Statistical Association: “Statistics is the science of learning from data and of measuring, controlling, and communicating uncertainty.”, and the official statistics on global poverty completely lack the element of uncertainty. The second cornerstone of the report is the proper consideration of trends and not levels of global poverty. This is linked to the strict mandate the Commission had been given; for a detailed critical exposition on this point see Moatsos (2018b).

<sup>45</sup>This chapter is joined work with Achilleas Lazopoulos (Institute for Theoretical Physics, ETH Zürich).

<sup>46</sup>See Atkinson (2016, Table 11); future applications should account for all the error sources therein.

rate of 23.5% (with 95% CI: 19.9%-27.4%) and in 2015 11.65% (with 95% CI: 8.7%-15.5%).<sup>47</sup> The CBN method identifies an overall reduction in the global poverty rate from 1990 to 2015 of 34.4% at a 95% confidence level, not too far from the 50% target of MDG1, while the dollar-a-day approach does not identify any poverty reduction at the same confidence level.<sup>48</sup>

More generally, the method of micro-simulation used in chapter 4 relates to data problems that should not remain confined within verbal reservations expressed in the body text of manuscripts, papers and articles, but should be embedded into the final estimates, figures, and tables. Otherwise we risk at drawing considerable less attention to the heart of the matter which is the empirical uncertainty over the provided estimates.<sup>49</sup>

Chapter 5 takes a step back from the global poverty estimations to provide with the necessary data required for making a long run poverty exercise possible from the perspective of income distributions. This chapter in an expanded version of the work done by Zanden van et al. (2013).<sup>50</sup> A variety of indirect methods are used to estimate income distributions for years and countries where such data are missing.<sup>51</sup> Most of the new estimates, compared with the prior available sources, are obtained by regressing income distribution on the coefficient of variation in height estimates, exploiting the biological channel where higher inequality in available resources among the population in early life links to a higher inequality at height variation.

By gathering all the data on income distributions we compute the evolution of global income inequality. First, the unweighted average of within-countries income inequality in 1820 and 2000 is the same at a Gini index of 0.45.<sup>52</sup> Second, the world Gini index in the 20th century is higher than in the 19th century, and has remained constant for the better part of the 20th century at about 0.6. Third, the driver of evolution of global inequality through time is the between-countries inequality component, although its role vis-a-vis the within-countries inequality component changes frequently. And fourth, the correlation of within-countries inequality with gross domestic product (GDP) per capita is positive during the 19th century and

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<sup>47</sup>Do note that for reasons of comparability, the exact definition of the poverty line follows the definition used in chapter 3, slightly adapted so that in 2015 the CBN and dollar-a-day approaches produce similar average estimates.

<sup>48</sup>For estimates about the possible success of the Sustainable Development Goals see Crespo Cuaresma et al. (2018).

<sup>49</sup>The same applies for uncertainties implied by the definitions of concepts that one tries to estimate its values.

<sup>50</sup>All authors in that article are co-authors of this chapter as well.

<sup>51</sup>See chapter 5 for the details.

<sup>52</sup>The Gini index is the most widely used index to measure inequality in an income or consumption distribution. A value of 0 represents total equality where all people have the same income (or consumption), and a value of 1 indicates total inequality where one person has all the income.

then turns negative during the better part of the 20th century.

Chapter 6 returns the focus to global poverty measurement, and provides the first application of a cost of basic needs approach on a global scale and on the long run, covering the period 1820-2018. The method builds around the approach put forward by Allen (2017) for measuring extreme absolute poverty, and uses a digitized version of ILO's October Inquiry commodity price data (for 1924-2008) to achieve this. The poverty line is defined using a consumption basket that allows for a fixed number of 2100 kcal, 50 gr of protein, and 34 gr of fat, based on the conclusions of Allen (2017) who argues that richer diets result in unrealistic food quantities, while less rich diets contain high risk of malnutrition. On top of these food components, expenses on housing, heating and clothing are added by imputation based on Allen's estimates. This step circumvents the lack of global prices for those expenses on the long run. This shortcut is done at the expense of a higher uncertainty in the estimates.<sup>53</sup>

Perhaps the most striking result of this exercise comes from the total number of people living in conditions of extreme absolute poverty globally. According to my findings the total number is 757 million people in 1820 and 764 million people in 2018 despite all the progress in lowering the global poverty rate in the years in between.<sup>54</sup> In terms of poverty rates, in 1820 the global poverty rate stood at 76%, by the turn of the 19th century this rate drops at 60%, and by the turn of the millennium it drops at 25.5%. By 2018 the CBN global poverty rate stands at 10%. At the same time this research has identified the substantial uncertainty in the global poverty estimates largely as the result of most likely unrealistic price data in the pre-1995 China.<sup>55</sup>

## 1.5. General conclusions

The twofold goal of this thesis is (a) to develop an alternative approach to measuring global poverty using a cost of basic needs framework, and (b) provide the

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<sup>53</sup>For example, in some countries the poverty line seems unrealistically low, as in the case of contemporary Greece with a value of around 2.5\$/day, that it is unlikely that it would allow for the expenses in the consumption basket. Better data in the future will allow a more accurate appreciation of poverty using a global standard in some of the countries.

<sup>54</sup>Worryingly in the United States of America a similar finding obtains, with the number of people living in conditions of poverty in 1820 being at 5.2 million, and in 2018 at 4.9 million. For 2015 the global count in chapter 6 is 887 million, which is on the right side of the FAO estimate of the 795 million people that go by undernourished world wide (see above).

<sup>55</sup>In calculating the global result an average scenario is used, but more detailed research is required to estimate the evolution of poverty in China for that period. This problem is not specific to the CBN approach and it is similarly valid for the dollar-a-day results, but with the CBN approach the problem is identifiable.

empirical and methodological apparatus that make such an application possible for today, but also on the long run. At the same time, this alternative method is compared with the standard DAD approach in order to investigate the limitations of the DAD approach proposed in the literature. Further, in the development of this alternative approach the limitations of CBN implementations are identified, and possible improvements are proposed and empirically explored. By taking the required steps in order to materialize the main goal of this thesis a small number of general conclusions can be drawn with respect to the measurement and the evolution of global poverty.

First, this research strongly indicates that the Purchasing Power Parity used by the standard approach in global poverty measurement does not hold at the level of consumption habits relevant to those living in conditions of extreme absolute poverty. This has long been suspected by the critics of that method, and here in chapter 3 the evidence that support this intuition have been made available.

Second, the cost of basic needs approach is a feasible method for a global scale appreciation of poverty, as it has been shown in chapters 3, 4 and 6. It has the advantage of addressing some of the key points raised against the dollar-a-day standard. It avoids PPP exchange rates and consumer price indices information which do not reflect the consumption patterns for those living in conditions of absolute poverty. Further, the welfare level that a cost of basic needs method targets can be read off from its recipe, which is more directly interpretable than the living standard corresponding to “the equivalent of 1.9 international dollar per day in 2011 prices”. This transparency of the CBN method allows one to reflect over the adequacy of the living standard it encapsulates. Arguably all poverty lines used in this thesis, including the DAD as well,<sup>56</sup> fall short to measure poverty with at least two definitions of poverty according to the: (a) Universal Declaration of Human Rights as a person not having the means to achieve “a standard of living adequate for the health and well-being of himself and of his family, including food, clothing, housing and medical care.”<sup>57</sup>; and (b) Copenhagen Declaration by the United Nations: “[a]bsolute poverty is a condition characterized by severe deprivation of basic human needs, including food, safe drinking water, sanitation facilities, health, shelter, education and information. It depends not only on income but also on access to social services.”<sup>58</sup> It is surprising that international authorities, entrusted with the duty of measuring global poverty, do not attempt to operationalize these

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<sup>56</sup>Since it occasionally produces estimates lower than the CBN approach applied in chapter 6.

<sup>57</sup>Universal Declaration of Human Rights, G.A. Res. 217 (III)A, art. 25, U.N. Doc. A/RES.217(III) (Dec. 10, 1948).; In this case the CBN approach implemented here in chapter 6 does not account for medical care.

<sup>58</sup>Obtained from UN, Copenhagen Declaration on February 22nd, 2016; in this case the CBN method applied in chapter 6 does not account for most of the elements mentioned.

internationally ratified definitions, and instead resort to a handy measure such as the DAD.

Third, the differences between the CBN and DAD approaches from chapter 6 may not appear particularly striking on the aggregate global level, however the differences are more marked on regional and country level. The CBN poverty lines in chapter 3 identify more stark differences, mainly because of the difference welfare levels they target. In the long run estimates presented in chapter 6, the average mean absolute difference in poverty rates between the two methods is 3.2 percentage points in the period from 1820 to 2018. The direction of this difference is not fixed and it takes both positive and negative values with an average CBN estimate being about 2.6 percentage points lower than DAD. On a regional level the differences are more pronounced, with a mean absolute difference of 6 percentage points, and the mean difference at less than 1 percentage point. Overall, the CBN estimates remain lower than the DAD for the most part of the entire period, and it is only after 1990 that this trend is reversed. During the 1950s and up until the end of 1970s, CBN identifies lower levels of poverty after a stronger decline compared to DAD results. The strong post-1990 poverty reduction identified by the DAD method is present in the CBN results as well, albeit attenuated. Chapter 3 provides some evidence that suggest an even slower reduction if one aims at higher welfare levels than the CBN poverty line applied in chapter 6, e.g. if one adds more than a 3 square meters per person, or if education and health expenses are included, etc.

In any case, the most appropriate level for comparing the results of the two methods is neither the global or regional levels, but the country level; and for the years for which the most direct estimates of the CBN poverty line are available. In this case the mean absolute difference is 9 percentage points, and the mean difference about 1 percentage point. This indicates again that the difference can be either positive or negative and there is no fixed difference between the two methods that could be used to simply correct the DAD approach as if it is a simple bias.<sup>59</sup> Overall, global absolute poverty is found to be lower for most of the historical period compared to the available estimates by Bourguignon and Morrisson (2002) and the comparable DAD based results in chapter 6. In comparison to Bourguignon and Morrisson (2002) my estimates become higher after the 1950s, while in comparison to the DAD approach it is only since the mid 1990s that the CBN method produces higher poverty rates than the DAD approach.

Fourth, linking chapters 4 and 6 allows us to reflect on the impact that the less reliable data from pre-1980 era may have on the accuracy of our appreciation of global poverty. The general message of chapter 4 in this regard is that the impact of those less reliable, or more error prone, data will in all likelihood be limited

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<sup>59</sup>Another way of putting this is by asking the question of “how large is the possible difference between CBN and DAD?”, but I will not address this approach here.



upon the confidence interval of the estimated poverty rates. This can be argued on the basis of the impact that the various error sources bear on the size of the final confidence level.<sup>60</sup> From the perspective of the dollar-a-day approach, the largest source of error stems from its derivation method. For the CBN method additions of higher uncertainty values for the underlying error sources, have a relatively modest final impact upon the global confidence interval. This allows one to expect that relatively larger measurement errors from pre-1980 data would also have a limited impact upon the uncertainty of the global poverty rate in the past.

Fifth, it is clear that the methods developed in this thesis are rather complex and computationally involved. This could hinder their potential adoption by other scholars or the World Bank. There are two remedies for this unfortunate, yet generally expected, outcome: First, and on the short term, is that I offer in the appendix most of my results, and soon in an online appendix I will make available the results of all my estimates. Second, and more on the long term, chapter 4 was the material for a public engagement exercise which can be found at `GlobalPoverty.World`.<sup>61</sup> This application allows users to define their own version of a cost of basic needs consumption basket by setting the content of the food expenses, and defining the share of the non-food expenses in the total cost of the poverty line. Once the consumption basket is defined, the application evaluates it in almost all developing countries around the world for 1990 and 2015, and the user can see the progress between the benchmark years of MDG1. This is the first ever online poverty estimator that is based on a cost of basic needs approach, and it can be expanded to accommodate more complex and more finely tailored poverty lines to estimate the level and the trend between those years. Scholars and interested individuals may use this app to define their own CBN poverty lines and get immediate results without any programming or other inconvenience.<sup>62</sup> I look forward to developing this application further to account for more years following the method of chapter 6 and provide detailed estimates on global poverty for any year between 1820-2018. I also look forward to developing an R library that will assist scholars to apply this method with ease.

Sixth, robust and methodologically sound statistics for poverty from a global perspective are a sine qua non for addressing key development questions, e.g. 'to what extent does aggregate growth help the poor', and "what affects the growth elasticity of poverty". Those interested in the long run perspective of those questions will no less benefit from the alternative estimations of global poverty that this thesis offers for the same reasons. Furthermore, Bowley (1915) 'best test' for

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<sup>60</sup>See tables 4.3 and 4.4 in chapter 4.

<sup>61</sup>This initiative received seed funding from the Public Engagement Office of Utrecht University.

<sup>62</sup>Results are offered on a global scale only, but until I upgrade it to provide detailed country level results, I offer the possibility to send users detailed results via email.

progress<sup>63</sup> can be readily applied with the results presented in this thesis. Moreover, late Sir Tony Atkinson's ultimate book prescribes that: “[p]overty statistics matter because they motivate people to tackle a key challenge” (Atkinson, 2019), and this thesis brings a fresh perspective to the statistical arena of global poverty estimates. In addition, substantial financial decisions by aid agencies around the world, including the World Bank, are partially informed by global poverty estimates. The methods developed here offer a robust alternative that, although not perfect, in several aspects is immune to problems pertaining the current dominant dollar-a-day methodology.

Finally, the long run results of this thesis, namely those of chapters 5 and 6, and to a lesser extend the results from the other empirical chapters, offer no easy material from an analytical perspective. The general framework selected in this thesis is a descriptive one, mostly due to the nature of its methodological contributions. Although, decomposing and explaining in detail the identified trends on a global scale and on the long run is beyond the scope of this thesis, a few remarks can be still made.

In terms of global inequality, the good news is that the global distribution of income has turned back to a unimodal shape, from a bimodal intermezzo roughly in the period 1960-1990, implying that the huge gaps between the developed and the developing world during that period are substantially less stark. Clearly, the role of China in this regard is key. The negative side of the story thought is that, similar to the findings of Piketty (2014), the initial decrease of within countries inequality in the aftermath of the second World War is followed by an increasing trend since about the mid-1980s. The implications of this development to political stability and robust growth are currently a very active field of research (see for example the World Inequality Report of 2018 at <https://wir2018.wid.world/>).

With respect to global poverty, a key element missing from tracing and explaining its evolution is a proper method of decomposition between the active components: inequality levels, changes in the value of the poverty line relative to the average inflation, and growth. Such a decomposition would expand on Bourguignon's poverty-growth-inequality identity triangle that is applicable to the dollar a day approach (Bourguignon, 2004).<sup>64</sup> However, even without such a tool at hand, some key points can be highlighted. In all likelihood the 19th century industrialization and globalization played a key role in the radical poverty reduction observed in the Western countries between 1820 and 1920. But we should not forget that poverty rates in the Western World during the 1920s are similar to poverty rates in several

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<sup>63</sup>The test being the proportion of people that are in poverty; see the aforementioned quotation.

<sup>64</sup>Throughout the later half of my PhD trajectory I made effort to find the time to develop this tool, but it remains still confined in my long to-do list. I wish to thank Leandro Prados de la Escosura for reminding me the importance of such a tool at the 2019 OECD meeting in Paris.

Sub-Saharan Africa countries of the recent period. In the most recent period, we already know that the main driver of poverty reduction was the acceleration of the most populous economies of India and, most importantly, China. This idea is corroborated by the results presented here, although, as implied above, the exact size of the role China played in terms of extreme absolute poverty reduction globally requires more scrutinization. From a historical perspective, this thesis shows that extreme absolute poverty had lower incidence during the 19th and the best part of 20th century as previously thought, while since about the 1980s the reverse obtains. More research is required to investigate this diversion. Moreover, one may reasonably expect that the role of future poverty developments in SSA would play a more important role because of the current and expected population growth rates. Available projections from UN's World Population Prospects indicate that SSA will increase as a share of global population from 14% in 2020 to 22% by 2050.

## 1.6. Future concerns and research

The United Nations agenda on eliminating global poverty,<sup>65</sup> building on the MDG1 early success momentum, may give the impression that (early) success may well happen again. Unfortunately there are many reasons why this may not be the case. On the top of the list one can consider the impact of climate and its link to potential food crisis in the near future as a threat to the improvement of the living standards among the least well-of population groups. This point is argued by the United Nations Intergovernmental Panel on Climate Change (IPCC).<sup>66</sup> Water scarcity is another threat for future living standards, as United Nations estimates that by 2025 1.8bn people will “be living in countries or regions with absolute water scarcity, and two-thirds of the world’s population could be living under water stressed conditions.”<sup>67</sup> Also recent experiences in developed countries indicate that even in countries that have long escaped the grip of extreme absolute poverty, intentional or unintentional policy implications, may well lead sectors of the population into extreme poverty.<sup>68</sup> These events can very well steer the progress against global poverty in the wrong direction.

With respect to the current constraints in global poverty research, it is important

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<sup>65</sup>Sustainable Development Goal 1.1 states that: “By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than \$1.25 a day” .

<sup>66</sup>The report can be found at: <https://www.ipcc.ch/srccl/>.

<sup>67</sup><https://www.un.org/waterforlifedecade/scarcity.shtml>, last visited on December 12th, 2019.

<sup>68</sup>See for example the findings of the results of the visit in USA by the UN rapporteur on extreme poverty and human rights, and the negative impact of recent austerity in the UK poverty according to the UN.

to starkly point out that independent scholars do not have access –or a clear way of acquiring access– to the best available distributional data used for estimating global poverty. According to Ravallion (2016a, p.352) the publicly available PovcalNet data are part of a larger and more detailed data set called the International Income Distribution Database (I2D2). Its use is restricted, and it is only available to World Bank researchers. The former director of the World Bank Research Group Martin Ravallion remains hopeful that this will change, and in his recent book write that: “[a]t the time of the writing I2D2 was not publicly available, but this will hopefully change soon.” (Ravallion, 2016a, p.352, fn.56). At the same time price datasets with global coverage of the type and quality of the International Comparison Program (ICP) <sup>69</sup> are much needed for more complete and reliable implementation of CBN global poverty estimates.

Moreover, not so long ago Ravallion and Chen (2011) have invigorated the issue of connecting the relative and absolute poverty concepts on the global level. They built on previous work by Atkinson and Bourguignon (2001) who were the first to conceptualize and empirically estimate global poverty from both relative and absolute perspectives. However, both rely on the dollar-a-day approach to expand an absolute poverty measure with relative poverty elements. This way all the criticism on the dollar-a-day method also applies to those extended approaches. The CBN framework can also be used in the future as a basis for unifying global poverty measurement with both absolute and relative considerations.

A more theoretical question comes from the strict application of any single valued monetary poverty line in a given country at a given year. It is hard to argue that someone having 1 cent a year more than the poverty line is not living in conditions of poverty. Especially when considering the large uncertainties discussed above (and in chapter 4 more extensively). In principle, such a strict application of a poverty threshold appears as a rather authoritative and thereby questionable choice. Fuzzy approaches to poverty may provide a useful solution for global poverty research as well.<sup>70</sup>

Another useful theoretical distinction can be made by differentiating between those in need, and those living in conditions of poverty. The former may still escape the later condition for example by means of social transfers. The latter though cannot. It is not so clear that people that somehow achieve a living standard above a certain threshold do so by their own means, for example they might just be able to bear these costs via social transfers; those individuals are in need, but manage to live in materialized conditions slightly above a threshold. The mere fact that they are in need of assistance is an indicator that they are poor that manage to escape

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<sup>69</sup>ICP works under the auspices of the World Bank, and is the authority that produces the PPP exchange rates.

<sup>70</sup>For the theoretical foundations and some applications on poverty see Betti et al. (2006).

living in poverty conditions via assistance. Unfortunately at the moment those are not estimated separately in global poverty research.

Finally, the methodological apparatus developed in this thesis may find further applications outside the field of poverty measurement. For example it can also be applied in research on (historical) real wages. Since the main point in estimating real wages is –in common with poverty research– to compare wages against a meaningful and equivalent standard, the CBN approach offers this possibility. Such an application could become a good example of indirect cross-topic methodological benefit.<sup>71</sup> Especially since the point of departure in this thesis is inspired from the work of Bob Allen in the real wages literature.

## 1.7. Final gloss

As recognized in each chapter separately, any remaining errors in the text or the results are solely my own (or shared with my respective co-authors). That said, I wish to acknowledge that in my efforts to reduce errors in the underlying data (price data in particular), I have exhausted my possibilities to identify them by contrasting with levels and trends in the prices of other items in the data set. In this effort, I didn't look behind things that did not look suspicious and maybe some errors have survived there as well; hidden in plain sight by appearing ordinary.

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<sup>71</sup>At the 2017 WEHC in Boston the session on real wages that I co-organized with Bob Allen, Jan Luiten van Zanden and Pim de Zwart, we presented early examples of such an application. In the near future, I hope that we will be able to deliver more on this adjacent strand of research.



## Chapter 2

# The Debate on Measurement

by Michail Moatsos

*“Je n’ai fait celle-ci plus longue  
que parce que je n’ai pas eu le  
loisir de la faire plus courte<sup>1</sup>”.*  
Blaise Pascal

In estimating the incident of global poverty, both contemporarily and historically, one needs to reach far into the domain of assumptions and second best approaches. This chapter navigates the reader through this methodological jungle. Some of the issues discussed below are partially also covered in the more specialized chapters that follow. Here, however, enough length is dedicated so that the interested reader gets a more firm introduction to the various issues involved. This section although extensive is not exhaustive, as several of the problems discussed below can fill lengthy chapters on their own. Overall, the focus is solely on the absolute poverty approach, which is the dominant in the global poverty literature.<sup>2</sup>

### 2.1. A critical literature review

The standard rule in this literature, since the early 90’s, is the application of international dollars as the reference currency for the international Poverty Line (iPL)

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<sup>1</sup>“I would have written a shorter letter, but I did not have the time.”

<sup>2</sup>There are only a handful of exceptions in terms of non strictly absolute global poverty: Atkinson and Bourguignon (2001), Ravallion and Chen (2011), and Ravallion and Chen (2017).

(Ravallion et al., 1991a).<sup>3</sup> All contributions rely on estimates based on purchasing power parity (PPP) exchange rates. Those exchange rates express the dollar purchasing power equivalent of –currently– almost all currencies around the globe, and they differ from the market exchange rates since they account for the fact that in less economically developed countries local currency has higher purchasing power due to the relative cheaper non-tradeable goods (such as rents and various services) which are not reflected in market exchange rates that depend on tradeables.

A few years ago, Dhongde and Minoiu (2011) summed up the activity regarding estimates of global poverty, and table 2.1 partially reproduces it, and provides an update based on new articles since. Dhongde and Minoiu (ibid) conclude that studies of global poverty estimates are not comparable. Methodological differences, countries in the sample and sources used, result in occasionally vast different estimates. Even when the same poverty line is applied, this is done only in name. The choice of the data that this poverty line is applied to has decisive impact on the final result. For example, some authors favor the use of income while others favor consumption. Both may be taken from National Account Statistics (NAS) or taken from the household surveys that also provide the data on the distribution of income or consumption. Since those variables are typically far from identical, by choosing among them one practically identifies substantially different population groups as living in conditions of poverty (Deaton, 2005).

### 2.1.1 Pioneering the research field

Ahluwalia et al. (1979) pioneered the field of objective global poverty measurement, and provided estimates for 36 developing countries in 1975. The poverty line (PL) applied was equivalent to the income per head of the 46<sup>th</sup> percentile of Indian population. India was selected to form the basis of the poverty line because it was the largest country in the sample, and “one of the best studied developing countries” (p.304, ibid). To obtain data on income the country’s per capita real GNP was used, and for converting between various currencies to common dollar denomination the results of the International Comparison Project as published in Kravis et al. (1978) were used. Thus all per capita GNP levels were converted in dollars in 1970 U.S. prices. This translated the selected poverty line to be 200 PPP dollars in 1970 U.S. prices. The most populous country at the time, China, was not included in the study. For 25 out of the 36 countries distributional data were at the time available, and for the remaining 11 the authors imputed the distributional values by using the Kuznets hypothesis<sup>4</sup>. Their measure of poverty throughout the

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<sup>3</sup>There has been one partial exception in Chen and Ravallion (2010) who add the “PPPs for the poor” calculated in international rupees by Deaton and Dupriez (2009).

<sup>4</sup>Kuznets hypothesis posits that at the initial stage of development where a transition from agri-



developing world resulted in an estimated rate of 38% for 1975.

Table 2.1: Chronology of global poverty studies

Global poverty study	Years Covered	No. of countries & Focus <sup>a</sup>	Database <sup>b</sup>
Ahluwalia et al. (1979)	1975	25, Developing	World Bank Data Bank
Ravallion et al. (1991a)	1985	22, Developing	World Bank
Chen et al. (1994)	1985-1990	44, Developing	World Bank / WDR
Ravallion and Chen (1997)	1987-1993	67, Developing	World Bank / WDR
Chen and Ravallion (2001)	1987-1998	88, Developing	World Bank
Bourguignon and Morrisson (2002)	1820-1992	Groupings <sup>c</sup> , Global	WIID, Historical
Bhalla (2002a)	1950-2000	149, Developing	World Bank, PWT
Chen and Ravallion (2004)	1981-2001	97, Developing	World Bank
Sala-i Martin (2006)	1970-2000	81 (138 <sup>d</sup> ), World	WIID, DS, PWT
Pinkovskiy and Sala-i Martin (2009)	1970-2006	191, World	DS, PovcalNet, WIID
Chen and Ravallion (2010)	1981-2005	115, Developing	WIID, PWT
Zanden van et al. (2011)	1820-2000	39-99 <sup>e</sup> , World	WIID, Historical
Pinkovskiy and Sala-i Martin (2016)	1992-2010	39-99 <sup>f</sup> , World & Developing	PovcalNet, WDI

<sup>a</sup>Countries for which distributional data is imputed are not included. It also refers to the maximum number of countries in the sample, which does not mean that for each year a study covers there are surveys available for all the countries in their sample. Focus refers to whether the paper focuses on global poverty, or on a mix of developing and developed countries, or more explicitly on poverty in the developing world.

<sup>b</sup>Note that all articles rely on various additional imputations; PWT: Penn World Tables; DS: Deininger and Squire (1996); WDR: World Development Report; WIID: UNU-WIDER World Income Inequality Database; Historical: various research studies; PovcalNet: online poverty calculator by the World Bank.

<sup>c</sup>Varies with the observation year.

<sup>d</sup>For 81 countries the author has data for more than 1 observation year, and the remaining country-years are imputed. An additional 29 countries have at least one distribution available for the entire period, and the remaining country-years are imputed. To reach the total 138, an additional group of 28 countries is included with pure imputation techniques.

<sup>e</sup>Varies with the observation year.

<sup>f</sup>Imputation is used extensively.

## 2.1.2 Household Survey based poverty

In their 1991 dollar-a-day poverty line reference paper, Ravallion et al. (hereafter also RDV) added a twist to the Ahluwalia et al. approach in their attempt to estimate poverty in developing countries for 1985. Being unsatisfied by the use of

culture to an industrial economy takes place, there is a natural increase in inequality that—as development continues—it will eventually be brought down at the long run equilibrium for inequality. See the discussion by Zanden van (1995) and Milanovic (2016), and also Kuznets (1955) for the original idea.

only one country to define the poverty line, they proposed instead to use the average of a bundle of low-income countries for which data were available at the time, thus limiting the sensitivity of the results to the variation of the poverty line in one country. Based on the 1985 PPP exchange rates by Summers and Heston (1988) and data on the national poverty lines from a group of 33 developing and developed countries, their econometric estimation predicts a 0.76\$-a-day minimum absolute poverty line (in 1985 prices), which is marginally higher than the poverty line of India. However, they point that the “absolute poverty line for low-income countries is \$31<sup>5</sup>, which (to the nearest dollar) is shared by” Indonesia, Bangladesh, Nepal, Kenya, Tanzania, Morocco, Philippines and Pakistan. Thus they settle for an average PL of countries that had their national poverty lines (NPLs) closely grouped according to their PPP dollar converted value.<sup>6</sup>

Their methodological framework starts from the premise that every national poverty line consist of two components: the absolute, which is fixed through time and countries, and the relative component which evolves as a result of economic development. Thus the original goal the authors set for themselves is to isolate the absolute component and use it as the iPL. However, their decision to settle for an average is in itself a deviation from the original goal of their paper.<sup>7</sup>

Contrary to Ahluwalia et al. (1979), who used GNP per capita from the National Accounts Statistics (NAS), RDV use consumption as reported by household surveys (HHS), or income as a second best choice if consumption was not available.<sup>8</sup> Since not all the distributional data available were for the year 1985, they extrapolated distributions from nearby years using an econometric model with a set of social indicators for 64 additional countries on top of the 22 for which they had timely distributional data.<sup>9</sup>

Overall, RDV estimate that for 86 developing countries in 1985, the poverty rate was 33%, with a 95% confidence interval between 27.9 and 39.2%.<sup>10</sup> They

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<sup>5</sup>Which translates to \$1.02/day and it is what will eventually be called the dollar-a-day poverty line.

<sup>6</sup>Revisions of PPP rates show that those clustered NPLs are not as close to one another as found by the PPP rates being available to the authors. For instance, due to the revision of India’s PPP rate in Summers and Heston (1991) the case that the Indian PL at 1985 was closer to the dollar-a-day value that thought of at the time.

<sup>7</sup>One implication with potential to bias the global poverty estimates is that as a result that deviation the iPL was set roughly 50% higher than the Indian NPL, by far the most populous country in their dataset.

<sup>8</sup>Subsections 2.3 and 2.4 discuss these methodological choices between HHS and NAS reported means, and income and consumption based HHS at length.

<sup>9</sup>Follow-up articles abandoned this econometric approach; see below for details.

<sup>10</sup>The only source of error they consider is the one introduced by the econometric model used in the extrapolation method to estimate the aggregate poverty for countries without distributional data. In their own words: “Allowing solely for imprecision due to the need to predict the poverty measures

also take good care to warn the reader about the overall accuracy of the results, characterizing them as “rough estimates only”. They also find that their aggregate poverty estimates are especially sensitive to errors in the PPP exchange rate for China. They calculate that a 10% overestimation in the measurement of the PPP rate for China, would result in a 5% overestimation of the aggregate poverty headcount, or 1 percentage point, which translates to 35 million people. This becomes particularly worrisome since the PPP source they rely upon did not include PPP exchange rates for China<sup>11</sup>, and they estimated the PPP values by extrapolation over the other available countries. In deriving the error terms of their estimation, however, they assume that the estimates which are based on actual distributional data do not contain any error component, no error term is linked to the PPP estimates, and no errors are included from the use of distributional data from different years (by imputation).

A few years later, Chen et al. (1994) revisited the problem of poverty with an increased sample of distributions reaching 44 countries “between 1981 and 1992, 19 of which have observations for two points in time within this period”. Compared to the RDV paper, the authors refrain from econometrically estimating the poverty rates in countries with no distributional data in their sample. Although they do make econometric estimations for missing distributional data when they have at least one distributional point for a country.

They also discuss the inappropriateness of simply using the national poverty lines and poverty rates for international comparisons. The point being that this way one can conclude that poverty rates between high-income and low-income countries is occasionally the same, such as in the case of their example of USA and Indonesia which both have 15% poverty rate in 1990 according to each country’s national poverty line. At the same time, they recognize the drawbacks of the use of PPP exchange rates, referring to the bias towards the prices of rich countries, and the problems in comparability of quality. They opt to the use of the dollarized international poverty line as estimated in RDV.

Regarding the welfare measure they apply, it is either the consumption as it is captured by the consumption based household surveys (26 of the 63 surveys), or income reported by income based household surveys multiplied by the ratio of private consumption to the GNP of the survey year (Chen et al., 1994, p.365). They also draw the reader’s attention to the fact that this later approach only adjusts the mean, but since possible changes in the actual distribution remain unaccounted for, the impact of this approach on the estimate of poverty is unclear. Chen et al. tested econometrically for any potential significant bias possibly introduced by including

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for those countries for which suitable distributional data are unavailable” (Ravallion et al., 1991b, Table 2, p. 354)

<sup>11</sup>Nor for Burma.

income based surveys, and concluded that there is none in their data set.

Again, since the household surveys do not necessarily coincide with the two years of comparison (1985 and 1990 in this case), the authors make the typical—in this strand of research— assumption that the survey closest to those dates is the best predictor for the actual distribution of those two years. They simply adjust the level of mean consumption by multiplying with the ratio of private consumption from the national accounts statistics between the year of survey and the year that survey was actually used for.<sup>12</sup>

In any case, several dollarized PLs were used, none of which showed any marked improvement in poverty rates in any region between the two observations years 1985 and 1990. Keeping the same dollar-a-day iPL as their poverty yardstick, they estimate almost the same figure as in the previous paper for the aggregate, namely 33.88% for 1985.<sup>13</sup> For 1990 the estimate “drops down”, by 0.36% which arguably is well within the error margins of the 1985 estimate, therefore one would be uncertain about any identified trends from the point estimates. The similarity in the aggregate poverty results between the two papers vanishes in the regional comparisons. The difference in the case of Middle East and North Africa (MENA) is the most prominent one, dropping from 31% to 4% in the later study. The previous estimate for MENA relied upon one actual survey for Morocco, and on extrapolation for the remaining, while the new estimate used 4 countries with surveys. The authors also attribute the big change in South Asia (SA), from 51% down to 37%, mainly to the updated PPP exchange rates in Summers and Heston (1991) compared to Summers and Heston (1988) for India.

An instructive approach is used to investigate potential bias from the countries included in the dataset for MENA and Sub-Saharan Africa (SSA), the two regions with particularly low population coverage. They find that the countries included in their sample have higher population weighted real consumption growth, compared with the ones left out and for which data exist. This indicates that the very low estimate for MENA may very well be downward biased. However, as the authors acknowledge, there is simply no information about the initial poverty levels in those countries. So by assuming, that the group of countries in the dataset was representative of the region in the initial date, and that growth is distribution neutral in

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<sup>12</sup>Only surveys that covered the entire population were used, with the exception of Ethiopia which had only one survey in the 80s and covered rural population only. However, 87% of the country were living in rural areas even in 1990 as the authors point out. Moreover, PPP exchange rate data for Eastern European and ex-Soviet countries were either unavailable or unreliable according to the authors. If PPP exchange rates were provided by Summers and Heston (1991) then the country was used. Similarly to their previous paper, the PPP estimates for China in Summers and Heston (1991) were indirect. China did not participate in the PPP estimates before 2005.

<sup>13</sup>Although the inclusion of two decimal points in the results implies a level of certainty in the results not warranted by the data or the method.

the excluded countries to “correct” the bias simply falls short to make the problem vanish.<sup>14</sup> Importantly, this time no error estimates of the main results are provided, and this unrecommended habit still persists to this day by other contributors and the official World Bank statistics on global poverty.

In 1997, Ravallion and Chen, updated their dataset and included for the first time countries from Eastern Europe and Central Asia (EECA). This posed an additional methodological issue since, as the authors readily acknowledge, if one applies an international poverty line relevant to low-income countries, this would yield very low poverty rates for EECA, while choosing a PL relevant to that region would give very high poverty rates to the low-income countries. Overall, using 1985 PPP dollars, absolute poverty in 1987 was found at 33.9%, in 1990 32.9% and in 1993 31.9%.<sup>15</sup>

On aggregate, the Chen et al. (1994) and Ravallion and Chen (1997) do not differ much for 1990, however, in a per region basis the results diverge considerably. For East Asia (EA), the rates are doubled from 15% to 29%. For Latin America and the Caribbean (LAC) there is a drop from 28% to 23%. In MENA the rate marginally increases from 3% to 4%, which still is a 33% increase. In SA the rates go from 59% down to 43%. And in SSA from 53% down to 39% all for the year 1990. Most importantly, this article identifies a 6-fold increase between 1987 and 1993 for EECA to a 3.5% poverty rate at the end of the period.

Those differences for the same year in 1990 emerge from a number of factors. One factor is the new available data. Another is that no extrapolation method was applied to include countries with no distributional data. Rescaling was applied when the survey was income based, and this was done by multiplying with the ratio of real consumption in the national accounts. For currency conversion the PPP exchange rates from PWT version 5.6 were used. According to the authors, here lies the source that shifts the estimates for EA so radically. Namely the upward revision for the PPP rate for China: If one uses PWT 5.0 the result for EA would be 14% instead of 29%. A revision for the PPP rates for India is also of important influence and brings down the SA aggregate. Other PPP revisions for MENA countries also drive the estimates downwards. Again, no error estimates of the main results are provided.

Arguably, in light of such big changes one should ask if under the same methodological strand, the repeat of the exercise of 1991 paper would be warranted for

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<sup>14</sup>Using more recently available data, the coverage for all regions is now considerably higher. However, the problem of missing distributional data still persists today and no perfect solution exists. For the imputation of poverty rates for years without necessary data, see chapter 6 for a work-around practical solution.

<sup>15</sup>Those are the aggregate results that exclude EECA in order to have a more comparable mix of countries that are used also in Chen et al. (1994).

estimating a new iPL, instead of recycling the old one. Those largely influential revisions of various PPP rates could imply shifts in the underlying poverty yardstick. A re-investigation of this would have been expected, however this will have to wait until the follow-up paper in 2001 on which we turn to next.

Chen and Ravallion (2001) expand considerably the dataset of surveys used to 297 surveys across 88 countries, and the PWT is abandoned as the source for PPP rates, and the PPPs from the World Bank Development Data Group are used instead. The underlying data for the 1993 ICP<sup>16</sup> round cover 110 countries, compared to the 60 countries represented in PWT 5.6 that was used in Ravallion and Chen (1997).<sup>17</sup> Similarly to Ravallion and Chen (1997), no imputation for countries without at least one survey was made and those countries were simply left out. For time alignment of the surveys the same method as in Ravallion and Chen (1997) was used.

In broad terms the same principle used in Ravallion et al. (1991a) was used to re-estimate the poverty line to be in line with the new ICP round data. In 1991, the dollar a day line was selected because for 6 low-income countries<sup>18</sup> the values of their respective NPLs in PPP terms were –to the nearest dollar (per month)– identical at \$31, and 2 other low-income countries<sup>19</sup> were close. Now this approach changes and the median of the ten lowest poverty lines is used instead. Those countries are different from the 8 countries of the 1991 paper, because of the new 1993 PPP exchange rates. Now the countries defining the international poverty line are: Bangladesh, China, India, Indonesia, Nepal, Pakistan, Tanzania, Thailand, Tunisia, and Zambia, and their median NPL is \$1.08 in 1993 prices.

Running the regression from the 1991 paper again, with a somewhat different structure,<sup>20</sup> the absolute poverty line obtained is \$1.05 in 1993 prices. From this result they conclude that the \$1.08 poverty line they derived is a “close approximation to the poverty line one would expect to find in the poorest country.” This translates to setting the dollar-a-day international absolute poverty line to \$1.08 in 1993 prices.

For the 88 countries in their dataset, 20 are represented with one survey, 18 with two and 50 with three or more within the 1980-1998 period; and their results cover the 1987-1998 period. As in Ravallion and Chen (1997) whenever there is only one survey the authors impute the estimates by shifting the mean consumption or

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<sup>16</sup>The International Comparison Program (ICP) operates under the auspices of the World Bank, and is the authority that produces the PPP exchange rates.

<sup>17</sup>However, for Ghana, Mauritania, Nicaragua, the Philippines, and Uganda, the PWT 5.6 PPPs are used instead of the World Bank's, because the application of the World Bank's PPPs implies poverty rates that are implausibly low (Chen and Ravallion, 2004).

<sup>18</sup>Indonesia, Bangladesh, Nepal, Kenya, Tanzania, and Morocco.

<sup>19</sup>Philippines and Pakistan.

<sup>20</sup>See the 2.2 for the details on the underlying formulas used.

income based on private consumption growth from the national accounts, and keep the Lorenz curve fixed.<sup>21</sup>

Overall, 181 out of 265 surveys were consumption based, and for the remaining surveys two strategies were applied. Most were re-scaled using the “one minus the national saving rate”, while about a quarter of them had mean consumption estimates available with which they replaced the average income of the surveys. This however falls short in accounting for the distributional differences among income based and consumption based distributions.<sup>22</sup>

The differences between Chen and Ravallion (2001) and previous estimates are substantial for the regional estimates. The most marked differences are for SSA, where the poverty estimates have risen to 50% up from 39% for 1993. The authors attribute this to the inclusion of additional countries with high poverty (Central African Republic, Gambia, Mali, Sierra Leone) and to the re-evaluations brought by the 1993 PPPs. On the contrary, the estimates in LAC decreased from 24% to 15% for 1993, and similarly for 1987 and 1990. For MENA the new 1993 estimate is half the old one, from 4% to 2%.

The next consumption based article on poverty covering the developing world comes by the same authors, albeit in different order, (Chen and Ravallion, 2004). Here for the first time the estimates go back to 1981, and end in 2001.<sup>23</sup> This paper covers 97 countries represented by 454 surveys.<sup>24</sup> As time coverage in this paper expands, it places additional pressure on the already limited data. For 1981 the coverage is quite low, with only 15 surveys up to 1983, and similarly for the last years of the period the number of surveys also drops. The problem can be also summarized by the population weighted mean date of surveys used for the years 1981 and 1984, which for EECA, SSA and MENA is actually 1988 (rounded to the nearest year).

The 1993 PPPs used in Chen and Ravallion (2001) are also applied here, but not all 97 countries in the dataset were covered in the 1993 PPP round. For some 26 countries the PPP estimates are based on interpolations from cross-country regressions as described in Ahmad (2003), while for India an update of the 1985 PPP

<sup>21</sup>For Kazakhstan, Kyrgyz, Latvia, Lithuania, Moldova, and Turkmenistan, instead of the unavailable NAS consumption data, GDP growth rates were used.

<sup>22</sup>The consumption distribution is substantially smoother than income distributions (Lopez and Servén, 2006).

<sup>23</sup>This paper works also with the 55th round of NHS in India, but due to some methodological issues related with what is called the “recall period” of the survey, the adjusted version of the survey’s results from Deaton (2003a). The authors report that using the official 55th round data the poverty rate for 2000 in India is 32.3%, and with Deaton’s adjusted data the poverty estimate becomes 34.7%. See Chen and Ravallion (2004) for more details on the issue.

<sup>24</sup>This translates to 59% coverage of the 776 surveys needed for a complete coverage, assuming that the surveys match the 8 benchmark years of the paper; however there is frequently a mismatch between benchmark and survey years.

round is used, and for China price levels from 10 cities are used.<sup>25</sup>

For the definition of the absolute poverty line the median of the 10 lowest poverty lines with the new PPP rates among the poverty lines available in Ravallion et al. (1991a) is used, providing a value identical to the \$1.08/day line from Chen and Ravallion (2001). It is not clear why the authors only focus on the poverty lines from the original set of 33 countries from Ravallion et al. (1991a), given the substantial new amount of new data on NPLs they have at their disposal.

The rescaling practice for the mean income when only one income distribution was available –followed in Chen and Ravallion (2001)– is now abandoned. The authors further show that comparing distributional data for both consumption and income that were available for 27 countries, gave no significant differences in terms of poverty rates.<sup>26</sup>

With respect to survey data availability, there are 9 countries with only one survey in the 1981-2001 period, 19 with two, and the remaining 69 countries have at least three. Again, when only one survey is available for a country, then the Lorenz curve is assumed fixed, and the average income or consumption is assumed to grow with the growth rate of real private consumption per person as recorded in the national accounts. When more surveys are available, then the same method is applied as in Chen and Ravallion (2001), with one difference: to estimate the poverty rate at a year between surveys they take the time-weighted average estimate from those two distributions after shifting their means using the real private consumption per person from NAS, with the distribution closest to the year of the estimate taking a proportionally higher weight.

The results of Chen and Ravallion (2004) show that the poverty rate with respect to the \$1.08/day poverty line has dropped by half during the 1981-2001 period throughout the developing world. Comparing with the results by Chen and Ravallion (2001), for the years these studies have in common, their similarity on the aggregate level is clear. They only deviate by one or two percentage points from 1990 onward, but with an increasing time trend on their difference. On a regional level there are several differences with Chen and Ravallion (2001).<sup>27</sup> Estimates for South Asia after 1990 diverge considerably with about 3 percentage points reduction in 1990 and 1993, and a drop from 42.3 to 36.6 in 1996. The almost 8 points reduction in 1999 is attributable in part to the different reference year,<sup>28</sup> although this alone should not be able to explain the entire difference.

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<sup>25</sup>Again as in Chen and Ravallion (2001) and for the same five countries mentioned previously, the PWT 5.6 PPPs are used instead of the World Bank's.

<sup>26</sup>It is likely that this is done in response to the remarks on the use of both consumption and income distributions by Deaton (2001).

<sup>27</sup>See section 7.1 of the appendix for the detailed tables.

<sup>28</sup>The year 1998 is reported in Chen and Ravallion (2001) instead of 1999, and the same mismatch of course occurs in all other regions as well for that year.



In Sub-Saharan Africa the estimates are also lower by 2 to 5.5 percentage points in the period 1990-1999. A downward revision is also brought about for Latin America and the Caribbean, which is most prominent in the period of 1987-1996, with a drop of about 4.5 points. As the authors mention, this drop is largely attributable to the absence of rescaling the mean income mentioned above. Smaller deviations in percentage points, but larger on a percent basis, appear for EECA, especially for 1987 and 1990.<sup>29</sup> MENA and EA differ less between the two studies. Overall the differences are the combined result of the new survey data, new countries that are included, and the non-rescaling of the mean income for countries that have only one available distribution.

Chen and Ravallion (2010) is the latest contribution in this literature from these two authors, that uses consumption based surveys to estimate the poverty rates on the entire developing world. In addition it makes the transition to the then latest ICP round of 2005. The 2005 PPP exchange rates they apply are the ones for “individual consumption expenditure by households” according to the 2005 ICP round of the World Bank (2008).<sup>30</sup> Those PPP exchange rates are different from those applied for the economy as a whole and are estimated specifically for the average household consumption. Every dollarized international poverty line is converted to the local currency in 2005, and then it is shifted in time correcting for price effects as they are captured by CPI, in order to be applied in a given country for a year other than the ICP benchmark year. The quality and the relevance of the “best available Consumer Price Index” to poverty estimates in each country naturally varies. The authors point to the fundamental role of CPIs, and acknowledge that since “the PPP conversion is only done in 2005, estimates may well become less reliable earlier in time, depending on the quality of the national CPIs”.<sup>31</sup>

The 2005 ICP round brought dramatic revisions to previous PPPs, which in turn brought similarly dramatic changes in the global absolute poverty rates.<sup>32</sup> This is the first time that India and China participated in the price surveys of an ICP round. In the 1993 round estimates for India were based on extrapolation from 1985 with the use of CPIs, and for China non-ICP sources were used with additional extrapolations similar to those used for India. Still a number of concerns remain for issues regarding the domestic representativeness of commodities, substantial “urban bias” in some countries, inappropriateness of the weights for the consumption habits of

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<sup>29</sup>Whether or not those differences are of some statistical significance is not obvious, since the standard errors are not reported.

<sup>30</sup>Previous articles discussed here used the PWT PPPs for consumption, with the exception of Chen and Ravallion (2001) which used the ICP consumption PPPs.

<sup>31</sup>Obviously the same concern applies for all the calculations that estimate global poverty with a method that uses PPP exchange rates, as it is done in the papers already covered here.

<sup>32</sup>The title of the Chen and Ravallion (2010) article is quite telling in this regard: “The Developing World is Poorer than We Thought, But No Less Successful in the Fight Against Poverty”.

the poor, and for the fact that PPPs are national averages. Partially addressing those issues for big countries, the authors split China, India and Indonesia in rural and urban areas and estimate different poverty lines for each. For China, since the ICP survey was carried out in urban areas only (covering 11 cities), they consider the ICP PPPs as urban PPPs and apply the urban/rural poverty line ratio for estimating a rural poverty line in local currency units (LCUs). For India and Indonesia the approach is similar in purpose, but less straight forward.<sup>33</sup>

A new ICP round requires for a new estimation of the poverty line within the dollar-a-day methodological tradition. The article by Chen and Ravallion utilizes the work done in Ravallion et al. (2009) (also referred to as RCS in the remaining of this text), covering 75 developing countries, much more than the 33 national poverty lines used in RDV almost twenty years before. Where possible national average poverty lines were included, compared to the use of rural poverty lines in RDV.<sup>34</sup> RCS estimate the international poverty line at \$1.25. They estimate this value as the mean poverty line of the group of countries with average personal consumption expenditure below \$60/month.<sup>35</sup> Alternative averages of poverty lines of the 10 or 20 poorest countries yield similar estimates for the international poverty line, namely \$1.22 and \$1.26 respectively.

The distributional data they rely upon consist of 675 nationally representative surveys covering 115 countries.<sup>36</sup> Least well covered are the regions of EECA and SSA during the 1980s. Due to the overall incidence of poverty in SSA the lack of data in the region carries more weight, and the projections used should be considered cautiously as they could bring bias to the estimates.

It is important to note that the estimates of the number of poor per region they provide are based on the assumption that the “countries without surveys are a random subsample of the region”. No further investigation of this claim is offered, such as the approach used by Chen et al. (1994, see above). To control for the possibility that some countries are no longer within the group of developing countries,

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<sup>33</sup>See Ravallion (2008a); Chen and Ravallion (2010) for more details.

<sup>34</sup>When rural and urban poverty lines are available, without an official NPL, the NPL used in is calculated as the weighted mean of the urban and rural poverty lines, using urban and rural real consumption (or income) shares as the weights, and using the poverty lines as the deflators. This formula was used for India, Benin, Ethiopia, Gambia, Kenya, North Macedonia, Mexico, Mozambique, Niger and Senegal.

<sup>35</sup>Chapter 4 provides a more detailed description of their method in pursuing the estimate of an appropriate confidence interval for the dollar-a-day iPL. The relevant countries are, starting from the country with the lowest personal consumption expenditure: Malawi, Mali, Ethiopia, Sierra Leone, Niger, Uganda, Gambia, Rwanda, Guinea-Bissau, Tanzania, Tajikistan, Mozambique, Chad, Nepal and Ghana.

<sup>36</sup>This translates to 65.2% coverage of the 1035 surveys needed for a complete coverage, assuming that the surveys match the 8 benchmark years of the paper; although this is not the case as a considerable number of them has to be shifted so that its used at a nearby benchmark year.

the grouping of a country in 2005 World Development Indicators as a developing one is used throughout the 1981-2005 period they cover.

Since the PPP estimates are calculated for the final year of the period, the time distance that one needs to cover back to 1981 using various CPIs becomes longer than ever before. This implies that the estimates may become less reliable the further back we go, to the extent that the average CPI mismatches with the price changes that those living in conditions of poverty face.

The new international poverty line of \$1.25/day shows a much larger incidence of poverty throughout the aggregate estimates, compared to the \$1.08/day in 1993 PPP (see the comparative table 7.1 in the appendix). However, the estimates show that the percentage of the population of the developing world living in absolute poverty was halved over the 25-year period between 1981 and 2005, falling from 52% to 25%. Their results also show a “bunching up” of people just above the poverty line. This translates to a high sensitivity of the aggregates that may result from a future “aggregate economic contraction (including real contraction due to higher prices)”. The champion of the poverty reduction is by far China. In 1981 the estimates show the incidence of poverty at 73.5% and by 2005 this number has been reduced to 8.1%. On the contrary, in SSA the poverty rates contracted marginally from 54% in 1981 to 51% in 2005.

The authors also provide a thorough investigation of the effect that the various changes in the underlying data have on their estimates. The contribution of the new PPPs, the new national poverty lines, and the new surveys are analyzed. The partial effect of new surveys is found very limited. Using the new survey database for 2005 with the old 1993 PPPs and old poverty line of \$1.08, then the initial rate of 17.6%, with the old database, is brought down slightly to 17.2%. Then, using the new poverty line data that move the international poverty line upward move the estimate from 17% to 29%. Incorporating the new 2005 PPPs have a net effect of -4% bringing the estimate to 25%. This net effect of the new PPPs is the result of two partial effects. One operating via the change in the global distribution that pushes the estimates upwards (+17 percentage points to 46%) and a balancing effect via the PPP revisions of the international poverty line that pushes the poverty rate downwards by 21% to the final 25%.<sup>37</sup>

Ferreira et al. (2015) offers the latest contribution within this strand of the global poverty literature, and updates the iPL using the latest ICP PPP round from 2011.<sup>38</sup> Apart from the update of the iPL value to \$1.9/day in 2011 prices, no

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<sup>37</sup>Chen and Ravallion (2010) offer estimates using the “PPPs for the poor” (P4s) provided by Deaton and Dupriez (2009) for a subset of countries. On aggregate those estimates do not differ considerably from the benchmark estimates, though the regional estimates differ more; additional details are discussed in section 2.2.

<sup>38</sup>For a thorough discussion of this article the reader is deferred to chapters 3 and 4. I avoid

remarkable changes occurred on the global aggregate in this PPP round as it happened with the previous one. Counter-intuitively Ferreira et al. did not repeat the entire exercise as described in Ravallion et al. (2009), but instead used the same countries, same "reference group" in their respective jargon, and took the average value of their NPLs. Other authors (Kakwani and Son, 2016; Sillers, 2015; Jolliffe and Prydz, 2016) have tried several other methods to estimate a global poverty line for the 2011 PPP round and all got values very close if not identical to the 1.9 estimation of Ferreira et al. (2015). This is what has also been called a "strange alignment of stars" by the at the time World Bank's chief economist Kuashik Basu (Atkinson, 2016, p.19). In any case, by choosing the same reference group as in Ravallion et al. (2009) their approach becomes a hybrid one with respect to the PPPs ICP round, as the reference group has been defined using the 2005 PPPs.

### 2.1.3 Mixed HHS/NAS global poverty research

After a long period of HHS consumption based estimations of global poverty, Bhalla (2002a) revisits the NAS-consumption-based approach. He is effectively building on the steps of Ahluwalia et al. (1979) in working with NAS data for anchoring the mean level of the distributions, but this time using consumption data instead of income. This is also the first attempt of estimating global poverty by a researcher not affiliated with the World Bank. Contrary to the previous contributions, his geographical domain is all countries with available data<sup>39</sup> regardless of their state in terms of economic development.

Bhalla argues that in order to estimate poverty rates using consumption data from National Accounts Statistics (NAS), one needs to consider how to correct for the notorious gap between the consumption based survey means and the consumption as they are captured in NAS.<sup>40</sup> He argues that the best way forward is to begin with a benchmark poverty line corresponding to the the 46th percentile of the Indian population distribution, as in Ahluwalia et al. (1979). Recalculated in 1985 prices it takes a value of \$1.25-a-day (not to be confused with the \$1.25 iPL of the World Bank which given in 2005 PPP terms). Next, he updates this line to \$1.30-a-day in 1993 prices by adjusting for the inflation in prices of U.S.<sup>41</sup>. His final figure

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extensive reference to this article here to reduce repetition.

<sup>39</sup>His dataset includes 149 countries with varying coverage.

<sup>40</sup>It is well known that there is a divergence among income (and consumption) measured by surveys and income (and consumption) based by national accounts statistics. See discussions by Ravallion (2000, 2003b); Sundaram and Tendulkar (2003); Koser (2010); Deaton and Zaidi (2002); Deaton (2010a) for more details, and the relevant discussion in section 2.4, also table 7.1 in Bhalla (2002a).

<sup>41</sup>This is one of several methodological issues in Bhalla's approach, as pointed out in Ravallion (2003a), whose reservations I find very convincing, but discussing them thoroughly is beyond the

for the international poverty line is \$1.5-a-day in 1993 prices after making some adjustments to bridge the methodological gap between using a consumption based poverty line and income based distributions (see below). The adjustments try to address under-reporting in the HHS, and the issue of the "missing rich". Those are the rich households that are missed by the researchers who execute the household surveys (e.g. living in gated communities), and instead are substituted by less than ideal substitute households in terms of overall household representativeness.

It is worth noting that the jump from the \$1.25/1.30-a-day line to the \$1.5-a-day, raises some methodological questions.<sup>42</sup> First, this 15% increase is based on the analysis of only one HHS for India in 1993/94, and its differences with the corresponding NAS consumption aggregates. Then this correction factor is imposed for every one of the 149 countries in his dataset, and for every year in a 51-years period. On the one hand, it is very unlikely that all countries for 1993/4 would require the same correction factor. And on the other, the application of this correction constantly in time goes against findings in the literature which identify an increasing trend in the divergence between NAS and HHS (Deaton, 2001, p.132). Arguably, what could be correct for India in 1993/94, may well overestimate or underestimate poverty in 1980 India, or China for 1990 or 2000 no matter which single adjustment one favors. If more surveys were used these corrections may have been less questionable.<sup>43</sup>

Second, to decide the necessary increase to account for under-reporting and

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scope of this chapter. Regarding this particular step Ravallion writes: "Bhalla's preferred approach of simply adjusting the old line upwards for inflation in the US ignores the fact that there has been (in effect) a PPP devaluation in poor countries relative to the US over the period. For example, China's and Indonesia's poverty lines at 1985 PPP are almost identical to their poverty line at 1993 PPP; India's poverty line at 1993 PPP is only 17 percent higher than its poverty line at 1985 PPP. Yet adjusting the 1985 \$1/day line for US inflation would entail an upward increase of roughly 50 percent. In other words, if one simply adjusts the \$1/day line for inflation in the United States between 1985 and 1993, then one obtains a poverty line that is well above those found in poorest countries. That would entail a re-calibration of the ruler." And regarding the Bhalla's approach to substitute HHS income or consumption information with NAS data he adds that "for decades, as have those for India (with the exception of a period in which a switch was made to the method Bhalla favors—the government of India was severely criticized within India at the time for cooking the books to show an artificial drop in poverty). And just about every other country in the world measures poverty this way [using the HHS micro-data]."

<sup>42</sup>I will only mention three issues here and for more details the reader may turn to the sources cited in the previous footnote. Of course the selection of the Indian PL per se is also questionable, as there is no clear reason why it would be a poverty line that would correspond to the same welfare level in other countries. This discussion develops in section 2.2.

<sup>43</sup>Interestingly when Sundaram and Tendulkar (2003) investigate the differences NAS/HHS for the same HHS, they reach different conclusions for the adjustment necessary for the poor end of the distribution, and conclude in favor of using HHS instead of NAS for this particular year to count poverty.

“missing rich”, Bhalla takes two steps. As a first step, he assumes that the “missing rich” are a constant 2% of the population.<sup>44</sup> As a second step, he assumes further that this constant 2% is consuming a constant 10% of NAS consumption. This claim is based on his calculation that the “average median consumption share of the top percentile in developing countries for the past 20 years is 7.5 percent; the average median share for the 99th percentile is 3.6 percent” and “[t]hus, a very safe assumption is that 10 percent of NAS consumption does not accrue to the surveyed population at all” Bhalla (2002a, p.120). No details are provided for those median figures, and the data from which they are obtained.<sup>45</sup> Of course if one assumes that it is 2% of the population that is missing, one has to estimate how much this upper 2% is consuming which is also missing from the HHS consumption data. Nevertheless, Bhalla adjust his PL by dividing \$1.3 with 0.9 to account for the missing 10% of NAS consumption from the “missing rich”, getting a PL of \$1.44-a-day. The rationale behind inflating his iPL is that this way the bias from using income from NAS instead of HHS based information will be accounted for.

The third issue, is the correction for the under-reporting differential among the bottom and the upper halves of the distribution. Bhalla gets his \$1.5-a-day PL by dividing with one minus how much more the top half of the population understates its expenditures compared to the bottom half. The “if”-statement that gives the exact figure has as follows: “[i]f the top half of the population understates its expenditures by 3.5 percent more than the bottom half”. The first and less important problem is that this 3.5% is not the right figure, if one follows his argumentation and his data, the actual figure is close to 6%.<sup>46</sup>

To estimate the figures of under-reporting of each income decile group Bhalla uses an approach that “preserve[s] the original pattern of distribution”. Clearly this method is neglecting a vital element: that under-reporting is higher per se for higher income groups, and for this reason the proportions in the original distribution cannot be the ones applied for the distribution of the unallocated difference among NAS and HHS.<sup>47</sup>

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<sup>44</sup>Interestingly, this is something that he calls a “fact”, without any sufficient evidence Bhalla (2002a, p.120), as his argument is that “[i]t is likely that such households constitute less than 2 percent of the population” Bhalla (2002a, p.119).

<sup>45</sup>e.g. if they come from raw data, and how many data-points are available, or they obtain from the imputed Lorenz curve method that he is using as explained below.

<sup>46</sup>According to figure 7.2 in Bhalla (2002a), the average correction required for the bottom half is 34.8%, and for the upper half 46.4%. This implies a 32% understatement for top (derived from:  $1 - 1/1.464 = 0.32$ ) and a 26% for bottom half (from  $1 - 1/1.348 = 0.26$ ). This in turn is a 6 percentage points of difference in absolute terms, and more in relative terms, but in any case not 3.5%.

<sup>47</sup>A clear indication of this can be found for example in his figure 7.1, showing that the mismatch between national accounts and food grains is only 10%, compared to 25% to 60% for other categories, and keeping in mind that the poor are more dependent on staple food than any other income group.

For estimating the number of poor under his \$1.5-a-day PL (in 1993 prices), Bhalla introduces a method he calls Simple Accounting Procedure (SAP). This procedure takes the raw distributional data in the form of quantiles and deciles and approximates a continuous Lorenz function. However, Bhalla picks a specific functional form for the Lorenz function, without a substantial testing procedure. It is tested for India, in the sense that it gives “low mean estimate error” for the Gini index of the Lorenz curve. Bhalla’s test for the percentile error of the SAP method is hard to be conclusive without testing other functional forms, and without an appreciation of the final error on the poverty estimate those errors imply. As noted by Ravallion (2003a), “a Lorenz curve model might come very close for the Gini index, say, but be way off for the poverty rate”, depending of course on where those errors of the estimated distribution are located.

Edward and Sumner (2013) point at two additional issues over the SAP approach. First that using a continuous function to model the Lorenz curve may lose information contained in the original data, in the sense that the resulting shares of deciles and quantiles may not be the same as in the original distribution. And second that attributing to each percentage of the population in a country the same mean income may lead to an underestimation of inequality, because the inequality within each percent of the population is by implication zero. In a population of 6 billion, a one percent deviation is 60 million more or less poor individuals.

Since one of the main purposes in Bhalla’s book is to provide poverty estimates for most countries (covering 149 of them) for a period of 51 years, imputation is required for the many income distributions that are missing. Indeed, as Ravallion (2003a) puts it, commenting on Bhalla’s coverage figures for the 1950-1980 period: “by Bhalla’s reckoning a country is deemed to have 100 percent coverage if it has just one survey over this 30-year period”.<sup>48</sup> For countries with one survey the distribution remains constant in the entire period, and for countries with

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In addition, the differences in the other categories imply that the between income groups differential is considerable and far from negligible. An additional argument in favor of an increasing under-reporting gradient is offered by Pinkovskiy and Sala-i Martin (2016) operating via the opportunity cost of the interviewee since the evident under-reporting in food items may be the result of the very time consuming procedure to document all the items in the questionnaire. For other less time consuming parts of questionnaires (e.g. health, education, etc) this under-reporting is not observed. Further, as Anand and Segal (2014) points out: “[f]ollowing Banerjee and Piketty’s (2010) finding that in India a significant part of the discrepancy between estimates of consumption expenditure in the national accounts and in household surveys can be accounted for by missing or under-reported top incomes”.

<sup>48</sup>In chapter 6 that covers global poverty from a long run perspective, I face the same problem, and I turn to the most complete historical source of income inequalities (provided by Zanden van et al. (2013) and expanded here in chapter 5), along with additional information from sources that became more recently available, as well as continuous synthetic inequality datasets. For details see chapter 6. Of course there is no perfect solution for missing data.

two or more distributions linear interpolation and extrapolation is used. In cases where only income distributions are available they are converted to a “consumption” distribution by a simple regression. No details are disclosed regarding this regression. For some countries without any distributional data the average regional quantiles were used for imputing these data. Finally, Ravallion (*ibid*) is very critical on Bhalla’s methodological choice of pooling together “distributions that differ in unknown ways in terms of their ranking variable (household or per capita) and in whether their observation unit is the person or the household”.

For estimating the level of consumption the NAS data from WDI were used, and when such data were not available PWT 5.6 was used instead to extract the consumption share from the GDP component in the WDI data. A missing observation was replaced with the most recent available, and when no consumption data were available then an average of the regional consumption share was used for imputing the data.

Bhalla’s preferred specification for measuring poverty, namely \$1.5-a-day in co-junction with NAS consumption data, demonstrate the fastest poverty reduction among all the PLs he is using.<sup>49</sup> The decrease in poverty rates that his results show is remarkable. From about 63% in 1950’s to down to about a 25% by 1990, and then another reduction by half by 2000 down to about 13%. Although the previous contributions discussed above focus on the developing world, and Bhalla provides world-wide estimates, a comparison with the results of (Chen and Ravallion, 2001) is still informative. Poverty reduction in Bhalla’s results takes place much faster for the \$1.08-a-day PL which is the only PL used by both studies. Since the coverage in Bhalla’s work includes the OECD countries with negligible poverty rates at such international PL’s, this implies that the corrections used by Bhalla, along with the use of NAS consumption, are decisive for his final results, although these corrections are not well supported by the empirical evidence he discusses.

The second independent study comes from Sala-i Martin (2006) who estimates the world distribution of income in the period 1970 to 2000, and subsequently calculates annual poverty rates using a variety of dollarized iPLs. The fundamental difference with the literature previously discussed is his strict preference to income distributions instead of consumption.<sup>50</sup> The article contains no discussion whether this approach is more appropriate, in comparison with other approaches, for deriving the global poverty rates. Further, he practically circumvents the conclusions by Deaton (2005) that survey consumption should be used in poverty measurement

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<sup>49</sup>Bhalla offers poverty estimates at several PL’s: \$1.25 and \$1.5 in 1993 PPP terms using NAS consumption, and \$1.08 and \$1.3 PLs with HHS consumption data.

<sup>50</sup>Income data are not taken from the survey data, but from the Penn World Tables 6.1 (Heston et al., 2002) in PPP-adjusted GDP per capita (and thus this paper is using the 1996 PPP benchmark year).



instead of NAS consumption, on the grounds that Deaton's point is specific for NAS consumption, and not to income that he uses. This response ignores the fact that typically NAS income is higher than NAS consumption and therefore Sala-i-Martin by choosing GDP per capita from NAS he only underestimates poverty even further; ergo Deaton's point is more relevant than in the consumption case.

The distributional data he applies are derived from Deininger and Squire (1996) and UNU-WIDER data as they were available at the time. The criterion of choice for the distribution data is to be income based, without further specification.<sup>51</sup> Also, as in Bhalla (2002a), both individual and household based surveys are used indistinguishably, making Ravallion's criticism on Bhalla applicable here as well. Given that the total number of country-year distributional data are falling by far short to be available for every country-year, Sala-i-Martin when more than one surveys are available for a country he predicts the quantiles of the unavailable distributions for that country.

For countries with only one year of available distributional data, the country is included, but its distribution is assumed fixed throughout. As the author mentions, those countries tend to be poor countries. For countries that have no distributional data available, the average quantile income shares of the "neighboring region" as he defines it, are used. On the complete dataset of imputed and survey based quantile income shares, they estimate the smooth income distribution by applying a Kernel Density Estimator.<sup>52</sup> In the end of this experiment a dataset that covers 138 countries on a yearly basis in the period 1970-2000 is constructed.<sup>53</sup> A methodological issue here is that, as Anand and Segal (2008) point out, the necessary conditions for applying a KDE are not fulfilled for the data used by Sala-i-Martin.

With the world distribution of income at hand, Sala-i-Martin uses several dollarized poverty lines to estimate global poverty rates. Since the paper is building around the 1996 PPP benchmark year, the relation with the poverty lines used in the consumption based literature covered above is not straightforward. No attempt is done to re-estimate the poverty line using the method in Ravallion et al. (1991a). Despite not following the defined methodology for international poverty lines, he makes the conversion of the \$1.02/day or \$372.3/year in 1985 prices from the original Ravallion et al. (ibid) to \$495/year or about \$1.36/day in 1996 prices. This conversion of course assumes that the changes induced by the change of the benchmark year on a per country basis follow the average U.S. price inflation. One needs

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<sup>51</sup>For example gross income, net income, monetary income, etc.

<sup>52</sup>This estimation method does not assume a specific functional form, and one needs only to specify the bandwidth for the estimate that functions as a smoothing factor.

<sup>53</sup>For more details on the imputation methods one can consult Sala-i Martin (2002a) and Sala-i Martin (2002b), along with a critical review from Milanovic (2002a), and cautionary note for the use of secondary sources by Atkinson and Brandolini (2001).

to actually test this assumption to gain confidence over this conversion.<sup>54</sup> This is the line he refers to as the “WB Poverty Line or \$1/day”.

Sala-i Martin also follows Bhalla (2002a), and adds 15% on top of this poverty line \$1.36/day in 1996 prices to correct for the use of national account per person data. This results to \$570/year or about \$1.5/day in 1996 PPP exchange rates. However, Bhalla is using consumption data for substantiating his adjustment, as we saw previously, while Salla-i-Martin is using income data, that despite the aforementioned methodological issues would in addition require more extensive adjustment if one follows Bhalla’s rationale. This use of income data becomes the a main source of divergence among their findings (the exact values shown in section 7.1 of the Appendix).

Trends in Sala-i Martin using those two lines are almost identical, since within the dollar a day methodology the most important factor for defining the trends is the evolution of the CPIs used (Klasen, 2009). The rate of poverty in the world is 20.2% in 1970 driven down to 7% by 2000 following the \$1.5/day line. While, according to the “WB Poverty Line or \$1/day” the rates are 15.4% and 5.7% respectively. In regional level, the differences with other estimates in the literature are considerably large.<sup>55</sup> Different poverty lines and PPPs, along with income based distributions and survey means anchored at NAS GDP per capita, result to a very positive picture of poverty, even compared to Bhalla’s work. The only exception is SSA for which the improvements are not as impressive as in the other regions.

Pinkovskiy and Sala-i Martin (2009) follow up on this work and expand coverage to 191 countries, this time using the well known log normality assumption to estimate the global income distribution between 1970 and 2006,<sup>56</sup> and from that the global poverty rate. Again the Deininger and Squire (1996) inequality database is used, along with an expanded version of the UNU-WIDER dataset. Similar to Chen and Ravallion (2010), they split India and China in rural and urban sections, and estimate each independently. The GDP data the PWT version 6.2 are taken as income for the baseline estimates (based on 2000 PPP benchmark year; Heston et al. (2006)), along with the ICP 2005 PPP round of the World Bank which the authors use for comparison.<sup>57</sup>

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<sup>54</sup>For a critical review of this approach see also Atkinson (2016).

<sup>55</sup>See the appendix for the exact values, tables 7.1-7.8.

<sup>56</sup>This approach assumes that income distribution follows a log-normal distribution. See Lopez and Servén (2006) for an empirical investigation of this assumption, which supports its use for income based distributions, but not for consumption based. Chapter 6 also relies on this assumption for its historical estimates.

<sup>57</sup>It should be noted that extending the PPP conversion for China back to 1970, using the old World Bank growth rates, implies that GDP per capita in China was \$308 in 2005 prices, a figure thought to be much lower than the income adequate for bare bones survival. For the use of this concept see Milanovic et al. (2007). However, as chapter 3 shows, the value of the necessary goods

There are 1069 income distributions used in total, 85 of which lie outside the period they covered, but they were used to allow for interpolation, instead of extrapolation. This leaves the investigation with 984 distributions for an exercise that requires 7067 distributions for 37 years and 191 countries, offering less than 14% coverage.<sup>58</sup> For this approach Milanovic (2002a) has argued that the extensive use of interpolations has worn out any variability in the sample. An argument that applies in all similar attempts that take this necessary step in estimating global poverty on a yearly frequency.

The authors use two basic poverty lines. One applies a literal dollar-a-day for 2006 and converting it to \$0.85 in 2000 prices.<sup>59</sup> And the second is a \$554 poverty line, that they obtain from the conversion of the original dollar-a-day in 1985 prices to U.S. prices in 2000.<sup>60</sup>

All the resulting global poverty rate trajectories show decreasing poverty rates throughout the examined period. The lower the PL the stronger the decrease observed.<sup>61</sup> The main point is that, as discussed above, the GDP-based global poverty estimates that the authors offer are typically lower in terms of levels, compared to HHS-based estimates, and faster in their speed of poverty reduction. Also, having results for a family of dollarized poverty lines leaves one question unanswered: What is the meaning of each additional line, and to what extent those higher PLs are capturing global poverty with common standards for every country? Or to put it differently to what extent the averaging nature of a dollarized international PL, meaning the vague link to a particular living standard in any country, becomes better or worse by increasing its level.<sup>62</sup>

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to achieve bare bones survival could be substantially lower than a dollar-a-day poverty line.

<sup>58</sup>To estimate distributions via extrapolation a variety of methods are used, and the details disclosed by the authors do not allow for a better understanding of which observations come from which method.

<sup>59</sup>Since \$365/day in 2006 is \$312 in 2000 U.S. prices, again raising the same methodological concern previously touched upon regarding the use of USA inflation rates to shift the value of the iPL in time.

<sup>60</sup>Pinkovskiy and Sala-i Martin (2009) convert a-1985-literally-dollar-a-day, so \$365 in 1985 prices, instead of \$1.02/day in 1985 prices that was used in Ravallion et al. (1991a), to \$554 in 2000 U.S. prices. However, according to <http://data.bls.gov/cgi-bin/cpicalc.pl>, \$365 in 1985 U.S. prices are \$584.14 in 2000 U.S. prices (conversely \$1.02\*365=\$372.3 in 1985 U.S. prices are \$595.82 in 2000 U.S. prices). The same \$584.14 in 2000 U.S. prices result obtains from the World Bank's WDI at <http://data.worldbank.org/indicator/FP.CPI.TOTL>. In addition they deliver their results for a family of poverty lines in 2000 U.S. prices, namely \$1108, \$1662, \$2770, \$4155 and \$5540 a year, corresponding to \$2, \$3, \$5, \$7.50 and \$10 a day in 1985 U.S. prices; the same year as the one used by the WB initial dollar-a-day poverty line.

<sup>61</sup>I will refrain here from detailed comparison of the results with others in the literature. For the tables that make this comparison see section 7.1 in the Appendix.

<sup>62</sup>See also section 2.2 that explains this marked inconsistency further, and chapter 3 that provides the empirics in support of the underlying claim.

The latest addition in the strand of mixed HHS/NAS global poverty research is provided by the same co-authors in Pinkovskiy and Sala-i Martin (2016). This paper is unique in its attempt to reconcile the differences among HHS (income or consumption) and NAS means (GDP per capita). This is done by using what they call a “trusted third party” of data as a reference point. Namely the nightlight images from the National Oceanic and Atmospheric Administration (NOAA).<sup>63</sup>

For their calculations they use as income the GDP per capita in 2005 PPPs from the World Bank National Account Statistics. Using their model with nightlight data they make an average among GDP data and HHS mean (heavily tilted towards GDP). For covering the 1992-2010 period, they use 701 income or consumption surveys from the PovcalNet database at the World Bank. This translates in using distributions with lower gradients (or lower inequality, such as those obtained typically from consumption data (Lopez and Servén, 2006)) combined with higher income per capita from the NAS. It is therefore expected to obtain the very low poverty rates they report (see section 7.1 of the appendix for the tables that compare the results).

A few additional points on the various methodological matters involved are worth noting here. First, the poverty line chosen is the World Bank’s \$1.25-a-day line in 2005 PPPs. As we have seen the dollar-a-day approach is a consumption based poverty line Ravallion et al. (1991a, 2009). No attempt to update this line in a way fit for the use of GDP data is done, leading to tentative underestimation compared to other global poverty rates in the literature. Basic methodological consistency implies that if someone would want to switch from the consumption domain of measuring poverty to the income domain, and still use a dollarized international poverty line, any re-use or re-estimation according to the approach of Ravallion et al. (1991a, 2009) is questionable unless the calculation of the iPL is repeated from scratch for income data based on the broad dollar-a-day framework as described in RDV and RCS.<sup>64</sup>

Second, the lognormal assumption is used in the calculations although now the underlying data from the PovcalNet website were made available at the time by

<sup>63</sup>In particular they use the data from the DMSP-OLS satellite program. Details of the econometric approach to attempt to empirically identify the ideal compromise, or the “true income” in the authors’ jargon, between the HHS and NAS sources will not be discussed here. Instead, I will focus on the overall methodological framework, the data used and the definitions of their concepts.

<sup>64</sup>In addition, the national poverty lines used in those articles to estimate the iPL are mostly estimated using caloric requirement plus some minimal additional consumption for necessities (see Ravallion et al. (2009) for details). Additional income e.g. from imputed income rents has to be incorporated properly both in the poverty line estimation and in the increase in income of each individual or household. In that respect Deaton (2005) has argued that imputed rents explain much of the discrepancies between the consumption means of HHS and NAS. If, as in the case of Pinkovskiy and Sala-i Martin (*ibid*), only the imputation takes place on the income side and iPL stays the same then a considerable underestimation of poverty is expected.

Dykstra et al. (2014b,a), and that assumption is found to be erratic when applied to consumption distributions (Lopez and Servén, 2006). Third, and perhaps most important, the distributional implications of the shift in everyone's income introduced by the use of the "true income", receive no attention by the authors. As we saw also in the case of Bhalla, there is no reason to assume that when correcting the difference between NAS and HHS means one should only change the average without changing "appropriately" the distribution as well. To implicate things even more than Bhalla does, the authors also use consumption based distributions together with largely NAS income data, further underestimating poverty, as consumption distribution are generally more egalitarian than income distributions (Lopez and Servén, *ibid*).

Finally, from this discussion stems an overarching lesson. Combining an iPL that is built to measure consumption-based international poverty, with welfare data from NAS is in all methodological likelihood not a proper way of estimating poverty.<sup>65</sup> Further underestimation obtains by using smoother distributions, such as those of consumption, in combination with NAS income data that contain irrelevant components, while at the same time one ignores the under-reporting differentials of the various income groups. Such use of GDP data implies that everyone gets equi-proportionally more, which is a point that needs to be demonstrated rather than assumed.

#### 2.1.4 Historical Research

There are two important articles that both follow an HHS/NAS mixing strategy and are unique in the sense that they have a long run historical approach starting in 1820. The works of Bourguignon and Morrisson (2002) and Zanden van et al. (2011) span across two centuries. For the first 150 years of that period almost no consumption based data are available.<sup>66</sup> In this regard there are not many options other than to combine the best available sources.

In 2002, Bourguignon and Morrisson, compiled together income distribution information over the long run to estimate the "Inequality Among World Citizens: 1820-1992". This kind of data of course are relatively scarce even for present day needs, and for the period before the second world war only a few direct estimates exist. The dataset was augmented backwards in the 19th century mostly by extrapolation from 20th century data (Zanden van et al., 2013). Beyond the uncertainty introduced by the imputation, there are also several important details and defini-

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<sup>65</sup>Despite the fact that two of the above articles are published in a top ranking journal (Sala-i Martin, 2006; Pinkovskiy and Sala-i Martin, 2016).

<sup>66</sup>This is a problem from which the current thesis suffers from as well, as it can be seen in chapter 6.

tions that change in the underlying methodology of the available HSS during this long period. These distributions are combined with data on GDP per capita, in 1990 PPPs, and population from the work of Maddison (1995).

The poverty lines they use are such that their results are equal to the estimates (at the time) made available by World Bank researchers for the \$1 and \$2-a-day poverty lines in 1985 PPP; the former line provides for estimates on “extreme poverty” and the later for “poverty”. This anchoring is done in order to roughly account for the differences between the methodology that estimates the poverty line, and the fact that they are using income distributions throughout. A main issue with this approach is that estimating poverty for such a long run reach using a fixed set of PPPs is highly unlikely not to add deviations from the price levels that are relevant for those living in conditions of poverty. Possible differences in trends between consumption and income surveys are not considered by the authors.

It is important to mention that this article by Bourguignon and Morrisson (2002), is the only one of the two articles discussed here that estimate global poverty in which the authors make an effort to provide their estimates with an appreciation of the involved uncertainties.<sup>67</sup> However, they consider uncertainty only in the underlying GDP per capita measures as a source of error in their estimates, and ignore any other, e.g. lack of country coverage, imputation of values, errors of the income distributions which are rough estimates for most of the early period, errors in the population data, the PPP exchange rates, etc.<sup>68</sup>

Zanden van et al. (2011)<sup>69</sup> work similarly as Bourguignon and Morrisson (2002) and use GDP per capita from the Maddison (2010) dataset<sup>70</sup>, together with a gross income dataset they compile for their long run analysis. Historical sources, combined with WIID data<sup>71</sup>, and a variety of imputation methods to estimate missing distributional observations which are used for the more distant years, are all combined to construct the most complete gross income inequality dataset at its time.<sup>72</sup>

As expected, the poverty estimates are the lowest for most of the years throughout the comparison tables among the articles discussed in this section, and are

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<sup>67</sup>The other one being Ravallion et al. (1991b), albeit considering only one error source.

<sup>68</sup>See chapter 4 and Atkinson (2016) for a discussion of other sources of uncertainty in global poverty estimates.

<sup>69</sup>In part due to the recognition of the shortcomings of the method mixed HHS/NAS as discussed here, the published version of the paper in Zanden van et al. (2013) does not contain the estimate for poverty, this is why I discuss here the working paper version of their article.

<sup>70</sup>The Maddison dataset is used to derive to two separate series of results: one with the “traditional” 1990 PPP, and for comparison, one also in the –latest available back then– 2005 ICP round.

<sup>71</sup>See <https://wid.world/>.

<sup>72</sup>For a discussion of the methods used, and for other underlying details, consult chapter 5 as that chapter expands the work done in Zanden van et al. (2011) and Zanden van et al. (2013).

shown in section 7.1 of the appendix. One should anticipate such a result since no calibration, or any other method, was applied to mitigate the methodological discrepancies between the WB dollarized PLs and the gross income distribution / GDP per capita approach that they apply.

## 2.2. An overview of the dollarized poverty line issues.

*“Poverty estimates for a country should not change simply because other countries’ consumption patterns or price levels have changed, nor because the consumption pattern or price level of goods that are not needed to avoid poverty have changed. A method of measurement that fails to satisfy this requirement is flawed.” Reddy and Pogge (2010)<sup>73</sup>*

In this section, I discuss the various issues regarding the definition and the estimation of an international poverty line in a common currency denomination. The international dollar per se has been used as the golden standard for common denomination by many authors and institutions. An approach that provides the exception to this rule is provided by Deaton and Dupriez (2009) that try to estimate PPPs for the poor, and focus on the developing world using international Rupees –instead of dollars– as the numeraire currency. Regardless of the underlying common denomination chosen, the implications of the various methodological decisions taken during the calculation of PPP exchange rates are discussed below in relation to the application of those rates in global poverty research.

### 2.2.1 Why PPP exchange rates should be avoided

The estimation of PPP exchange rates is a data intense, and methodologically demanding exercise. For this purpose a worldwide collaboration among the World Bank and national statistical authorities sets-up the framework of the International Comparison Program (ICP). For the latest round in 2011, 199 countries are covered, 53 more than the previous round in 2005.<sup>74</sup> This entails an enormous methodological and statistical endeavor, that includes considerable improvements in coverage and homogenization of the various processes compared to previous rounds. The question that remains though is not related so much with how well is the design of an ICP round, and the extend of the resources allocated to it, but if the resulting

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<sup>73</sup>Emphasis in the original.

<sup>74</sup>The next ICP round is conducted in 2017 but the results are not available yet at the time of writing this thesis, and are expected in late April 2020 (ICP Highlights, Issue 44).

PPP exchange rates, and the methodology that underlines them, are appropriate for use in global poverty measurement.

The World Bank warns about the application of PPP rates for poverty estimates, by acknowledging that PPP estimates “may not reflect the expenditure patterns of the poor” (TheWorldBank, 2007). The reason for issuing this warning is that the PPP estimates are calculated either for the economy as a whole or for *all* the households, and therefore in neither case reflecting the expenditure patterns of those living in conditions of poverty. A related example pointed out by Deaton (2001) is the 0.1 percent poverty rate in Thailand in 1997, which World Bank’s Chief Economist at that time, Joseph Stiglitz, has cited as “one of the consequences of the Asian economic miracle”. Deaton argues that this finding is a result of unsuitable PPP conversions, instead of an economic miracle. The point being that the unsuitability of PPP exchange rates is casting reasonable doubts over poverty estimates that make use of them. Similar warnings, albeit in different format, have been issued for the latest round of PPP estimates using 2011 as the benchmark year, that was published in June of 2014 by the then chief economist Kaushik Basu.<sup>75</sup> According to the Brookings Institution, preliminary calculations using the 2011 PPPs brings an immediate poverty reduction of between 25-to-50+ percent, depending on adjusting the poverty line or not; their method however ignores some fundamental steps thus producing marked differences.<sup>76</sup>

Overall, compiling a consistent PPP dataset is a challenge in itself, but taking the next step in building PPP datasets that “reflect the relative price levels of the goods and services faced by poor consumers” (Aten and Menezes, 2002) is an additional challenge which some scholars suggest that won’t be a feasible option. Klasen et al. (2016) conclude that “it would be best to consider alternatives to the current reliance on ICP rounds and the resulting PPPs.” Without going into the underlying formulas, I demonstrate in the following subsections a number of core reasons why one should indeed –as Klasen et al. recommend among others– abandon the use of PPP exchange rates in poverty estimates.

### **Consumption patterns**

In their seminal article Ravallion et al. (1991b, p.5) state that “[i]deally one would like to construct new PPP rates for the prices most relevant to the absolute poor, in which the prices of food-staples would clearly carry a high weight”. Before

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<sup>75</sup>World Bank’s Understanding PPPs.

<sup>76</sup>What Do New Price Data Mean for the Goal of Ending Extreme Poverty? at Brookings Institute, last accessed October 19th, 2018. Although clearly they have not followed the strict procedure in updating the iPL accordingly (as Ravallion has also pointed out for this approach). Thus their observations are largely overstated. See chapter 3 for the results according to the 2011 ICP round, as well as the comparison tables in the appendix (section 7.1).



them Ahluwalia et al. (1979, p.305) already acknowledged that the application of the Kravis ratio (which is how PPPs were called at the time) is more appropriate than market exchange rates in global poverty research, but other problems arise that replace the problems addressed. One concern relates to the likelihood that PPPs vary among various income groups within a country. Another element that concerned them was that the switch from market rates to PPP rates is based, among other things, on the undervaluation of services in developing countries, in turn this may well mean that “official exchange rates understate incomes of the rich more than of the poor”, since services are consumed more by the higher income groups within those countries. Averaging out this into a single PPP rate simply turns a blind eye to the problem, as it assigns to the poor part of the additional (compared to market exchange rates) purchasing power that should be attributed to the richer.

Theoretically, PPP comparisons may have a potential to become ideal once all the products in the calculations are representative for all participating countries. Obviously, this holds when one wants to compare countries. When the goal is to investigate how specific population groups in each country compare with their corresponding groups in all other countries, then again calculations should include representative consumption elements of those groups. In any case, the practice of the World Bank in estimating consumption PPPs ignores this point. Pogge (2013) provides an illuminating numeric example. Imagine a simplistic world where there are only three commodities: necessities, discretionaries, and services. Assume that the prices for these commodities in country X are 5, 6 and 1 respectively, and in numeraire country A respective prices are 3, 4 and 9. Pogge, calculates the PPP to be 1.55, meaning that each local currency unit (LCU) in country X is equivalent, in PPP terms, to 1.55 numeraire LCUs. If one however only focuses in necessities consumption, as one would when identifying the poor, X country’s LCU worths 0.6 numeraire LCUs. The implication of this, as they put it, is straightforward: “The Bank’s reliance on general consumption PPPs ensures that, wherever the actual price of necessities is higher than what such PPPs suggest, many who are very poor, relative to what they really need to buy, do not show up in the Bank’s extreme poverty statistics” (ibid).

As said, the above example is very simplistic, and assumes further that the three commodities consumed in the two countries are identical, and representative. More often than not, neither of the two holds exactly. Even when comparing similarly poor countries, the products that are necessary for survival may well be country specific. Deaton’s (e.g. in 2010, and 2013) favorite related example is that of teff in Ethiopia, which is rarely used anywhere else, and tofu in Indonesia. Both are basic food stuff consumed by the poor in those countries. But when one wants to compare the poor in the two countries, pricing appropriately those products is simply impossible, as there is no teff in Indonesia and no tofu in Ethiopia. There

are methods to estimate a “reasonable” price by regression, but those estimates cannot correct for the fact that any estimated price does not represent anything real. Those prices are simply statistically convenient structures that make the estimation of PPP exchange rates possible. The bias can work either way in those estimates.

Going back to the teff and tofu example, lets further assume that both of these products are consumed in country X, and then follow the steps taken by Deaton and Heston (2010): the price of teff in Ethiopia is  $P_{teff}^{Ethiopia}$ , the price of tofu in Indonesia is  $P_{tofu}^{Indonesia}$ , and in country X teff is priced at  $P_{teff}^X$  and tofu at  $P_{tofu}^X$ . Then the imputation method would give a parity of tofu relative to teff as the product of  $P_{tofu}^X / P_{tofu}^{Indonesia}$  (the parity of tofu between country X and Indonesia) and  $P_{teff}^{Ethiopia} / P_{teff}^X$  (the parity of teff between Ethiopia and country X). The conclusion of Deaton and Heston is that this estimation “is certainly arbitrary in the sense that the parity between two countries depends entirely on information from third countries”. This is of course a problem related to the nonexistence of important products in some third countries. The problem of course persists even in milder versions related to products that are less than representative of consumption patterns in a country. Again biases are introduced in the estimates. Those problems tend to be augmented when one needs to compare countries with dissimilar patterns of relative prices and expenditures.

Besides tentative differences in staple food consumption patterns, other GDP components that are “comparison-resistant” include government provided services, health care, education, construction, and house rental. According to Deaton and Heston, due to the importance of those GDP components their treatment can affect country wide and region wide PPPs. For the house rental component, the cases of Asia and Africa are treated differently than other regions. The implication of this difference in treatment is that housing volumes cannot be meaningfully compared between countries within and outside of those regions. For Ghana, Chad, and Malawi they estimate that the divergence in PPP rates when including or excluding the rental category can be close to 10 percent. Deaton (2010b, p.14) estimates that using a price-wise neutral treatment of the rental component a reduction of poverty count for 2005 “by more than 100 million people”.

When calculating PPPs the more one commodity is consumed, the more its price will influence the final PPPs. Pogge (2013) maintains that PPPs are influenced too much by the prices of commodities that are irrelevant to absolute poverty avoidance, such as luxury goods and services. Inversely, PPPs are influenced relatively little by the relevant necessities to those who live in conditions of poverty. Along the same lines Aten and Heston (2010) conclude that available household consumption PPPs is an improvement compared to the GDP (or economy wide) PPPs, as they exclude investments and government expenditure. However, still the average consumption patterns differ with the patterns of those that struggle for

survival in conditions of extreme poverty. They suggest that one could focus on consumption patterns of the poor, and the respective prices they face, but the problem is hard to solve due to unavailability of such data. Ravallion (2010a) criticizes the idea of pricing a single basket of goods implied by Reddy and Pogge (2010) and Aten and Heston (2010) on the grounds that consumption patterns differ among the poor in different countries (like in the tofu and teff example). However, this criticism holds only in the extreme case of rigidly fixed recipe in the space of products for pricing the consumption basket that would underlie a cost of basic needs poverty line, and as Allen (2013) argues, there is no reason why the baskets cannot adapt, e.g. to local price specifications by choosing the cheapest combination of products to achieve a specific goal.<sup>77</sup>

### Country (ir)relevance

PPP estimates are more reliable and accurate when the participating countries have similar consumption patterns and similar economic structure. The more the countries differ in these perspectives the larger the resulting concern for the PPP estimates.

Of particular concern are the unrepresentative high-end prices in poor countries, when one constructs PPP rates that include a mix of poor and rich countries. When one is estimating global absolute poverty figures using PPPs it follows that –as discussed above– the number of poor in one country will fluctuate based on the change in prices in a third country, even if nothing changed in the investigated country and the numeraire country (Reddy and Pogge, 2010). On this topic Deaton and Heston (2010) uses the example of consumption of wine. Considering the case that the expenditure share for wine in Cameroon is small, it is the case due to the application of GEKS calculations (see relative subsection below) that the price of wine in Cameroon will attract some of the price from France or other rich countries that consume more expensive wine. This would imply an overstatement of prices in Cameroon, and an understatement of its real GDP in PPP terms. The effect will not be that great since the consumption of wine in Cameroon has a small share. For other products with larger share the impact in understatement of real GDP would be larger.<sup>78</sup>

A related and rather unexpected issue is that of the global political balance in getting the final ICP calculations. As Deaton and Heston (2010, p.18) discusses the participation of Eurostat in the ICP rounds since 1980 is made conditional on

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<sup>77</sup>The approach of linear programming is used throughout this thesis to account for this issue. See the following empirical chapters on poverty for details.

<sup>78</sup>Of course in this example the issue of quality is not treated, but quality has similar problems as in the case of consumption patterns discussed here (Deaton and Heston, 2010).

ICP respecting the regional PPPs as estimated by Eurostat. This calls for additional fixity concerns that are political and not statistical in nature. Deaton estimates that without imposing this type of fixity constrains one gets a 6.6 percent higher real GDP for China for the 2005 PPP round.

### **The main point of Reddy and Pogge criticism on the use of PPPs**

The final step in the calculation of PPPs involves an adjustment that fulfills the so called “transitivity” requirement among the PPP rates for the various countries. This means that the PPP rate between say India and USA, for example, should be the same if it is estimated directly or via a group of third countries, say via Luxembourg. This final step influences the PPP rates not only with respect to the relative prices and spending structure of the numeraire country, but also with those from every other country (Pogge, 2013).<sup>79</sup> Or in the words of Pogge (2013) “The fact that an income suffices to meet basic human needs [in one country] is no assurance, then, that a PPP equivalent income in another country is similarly sufficient. In poor countries, prices of necessities are often higher, and prices of services lower, than what the PPP to the US dollar would suggest”.

This does not mean however that without imposing transitivity, the bilateral PPP rates would be more useful, as still commodities and consumption patterns of the numeraire country would influence the poverty status in all other participating countries. This relativity in the World Bank method cannot be accounted for. The dollar-a-day methodological approach supports the idea that it is possible to pinpoint a single common poverty line in a common denomination, when at the same time the PPP process itself, and the problems inert to the PPP estimation method, make evident that such equivalence is biased (towards an unclear direction), and most likely the bias is different for each country. This argument holds for every PPP dataset at its benchmark years. If one moves the comparison beyond the benchmark year an additional bias via the application of domestic CPIs, that have different consumption structure than the one implied by the ICP, and the prices that the poor face, affect the bias further. The further we go from the benchmark year, the PPP estimates become even less reliable for global poverty research.

The assiduous effort of Deaton and Dupriez (2009) in calculating PPP rates relevant for the poor –although has to some extent attenuated the problems mentioned above– for a number of reasons the PPP for the poor (P4s) they provide do

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<sup>79</sup>This translates to the methodological concern quoted in the beginning of this section, whether the World Bank categorizes a person as poor or not according to the iPL, it is not only affected by the available means of the person and the prices that person faces, but also on the prices and consumption habits of all countries participating in the ICP round. Deaton (2001) offers a relief with respect to this point, by indicating that the PPP rates pre- and post the imposition of the transitivity constraints are very similar.

not address the issues fully. On the one hand, as the authors recognize, there are problems that relate to the availability of data below their "basic headings". This means that the data they used in their calculations come in some form of aggregates and do not include the actual micro data of commodity prices and volume from the 2005 ICP round. On the other hand, consumption patterns and country irrelevance problems arise even if one focuses only for the developing world, excluding e.g. OECD countries, or considering only those basic headings that are arguably more relevant to the less poor. The fact that on aggregate PPPs and P4s give very close results according to Chen and Ravallion (2010), does not mean that the differences in a per region or per country basis are negligible as found in (Deaton and Dupriez, 2009, Table 16). The coincidence on aggregate brings no guarantees that would be so in forthcoming ICP rounds, especially if the underlying data below the basic headings become available for independent evaluation.<sup>80</sup>

### **PPP estimates using GEKS & GK**

There are two main sources of PPP estimates, the Penn World Tables and the World Development Indicators. PWT was GK-based (Geary-Khamis)<sup>81</sup>, and WDI is GEKS-based (Gini-Eltető-Köves-Szulc).<sup>82</sup> In a sensitivity analysis Ackland et al. (2013), have shown the impact of different methods in calculating the PPP rates. They conclude that the GK method understates the number of the global poor relative to the GEKS method. This is mainly due to the higher purchasing power attributed to the relatively poor countries.<sup>83</sup> From PWT version 8.0, some steps to addresses those concerns over previous versions have been made.

Reddy and Pogge (2010) argue that both methods may introduce artificial declines in poverty rates. For the GEKS method this bias operates via the rising share of services in consumption, because those services are relatively cheaper in poor

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<sup>80</sup>To date there is no similar attempt to that of Deaton and Dupriez (2009) for the 2011 ICP round.

<sup>81</sup>As of version 8.0 they changed their approach to a combination of methods. For the latest method underlying PWT see Feenstra et al. (2015).

<sup>82</sup>I follow the GEKS convention introduced by Deaton, in recognizing the priority of Corrado Gini in the conception of the method.

<sup>83</sup>This is achieved by the way the international price vector is computed, that brings the vector closer to the prices prevailing in the rich OECD countries, rather than the less affluent ones. This approach ignores the substitution for cheaper commodities that takes place in the poorer countries. Thus the income in poor countries is overstated, an effect dubbed as the Gershenkron effect. Further, in the GEKS method, the GEKS quantity index is the geometric mean of Fisher quantity indexes. In turn the Fisher quantity index is the geometric mean of the Laspeyres and Paasche quantity indexes. It is known that Laspeyres index shows a propensity to overstate the income of rich countries relative to the poor, and the opposite is true for the Paasche index. Apparently there is no guarantee that the Fisher index will be bias free as a result of taking their geometric mean. However, it is the case that the bias is smaller than the one introduced by the GK-method, as also Ackland et al. (2013) demonstrate.

countries compared to the rich. This brings about a decline in PPPs, and thus an artificial decline in poverty as a mechanical product of time. The bias in the GK method is driven by shifts in consumption from tradeables (e.g. food items, manufactures, etc.) to non-tradeables (e.g. housing, local services, etc.) that result in reducing the PPP of poor countries (and as a result also reduce their poverty rates as measured by the dollar-a-day method).

### **CPI implications**

The standard practice in poverty estimates is to apply the PPP exchange rates for the PPP benchmark year for each country. Then in order to get poverty estimates for any previous, or following, year the domestic CPI is applied for each country. At the same time it is widely accepted that the purchasing power equivalence does not necessarily hold with this CPI application (Chen and Ravallion, 2010). As discussed in Deaton and Heston (2010, p.27) the application of CPI will not match the PPP exchange rates derived in the next (or any previous) benchmark year. This issue obtains, among other reasons, because of: (i) the differences between items priced for the domestic index and the items priced for the ICP rounds, (ii) the differences in the geographical coverage where price collection takes place in domestic and ICP rounds, and (iii) because this step takes place for each country separately and no transitivity constraint is applied as in the calculation of PPP exchange rates.

The implication of this can also be understood from the perspective of the iPL. To come up with the poverty rate for each country, the iPL is converted to local currency units (LCUs) using PPP rates for the benchmark year. To estimate the LCUs that correspond to the iPL line for the year before the benchmark its value is discounted by the domestic CPI rate, and so forth for any previous year. This is done for all countries under inspection. In principle then the iPL moves into different trajectories for each country separately for the reasons mentioned above.<sup>84</sup> The larger the distance from the benchmark year the wider the implications of domestic CPI application on the global poverty estimates. Clearly, this has a stronger impact in more long run estimations of poverty, and the further away we move from the ICP benchmark year, the larger becomes the concern regarding the assumption that an iPL maintains purchasing equivalence all over the world. Ideally for the dollar-a-day method, in this regard, one should have a new ICP round every year producing PPP exchange rates that would be used only for that year.

These are the reasons why Chen and Ravallion (2001) argue when comparing the iPLs between 1985 and 1993 rounds, that “[i]n effect, the whole structure of relative prices (embodied in the PPPs) has changed”. So there is no direct way in

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<sup>84</sup>Therefore, the iPL in non-benchmark years is not the international one any more, as it has been domesticated by the CPI application and conversion to LCUs.

comparing iPLs of different PPP benchmark years, they simply belong to different price and quantities constellations.

As briefly mentioned above, an obvious, but nevertheless important, observation for the role of CPIs and each PPP update has been made by Klasen (2009). Comparing the changes between using different PPP benchmark years, and given that the available HHS are the same, the transition between PPPs affects the levels and hardly the trends. This is because the trends are mostly dictated by the application of CPIs in domestic terms.<sup>85</sup>

At the same time, with respect to the CPI composition per se, Pogge (2013) convincingly argues that national CPI “is influenced most by the commodities on which most is spent.” Which means in turn that a CPI is a plutocratic index in this sense, as those who spend more influence the index more. Arguably those products that are not consumed by the people living in conditions of poverty should not be part of a proper price index for tracing poverty. And the weights used to construct such a price index “for the poor” should be representative of the consumption habits of those same individuals. Typically this is not the case for the CPIs applied in the global poverty literature.

### **Errors in PPP**

Although the field of economics holds statistical significance dear, in global poverty research there seems to be little motivation in estimating, or disclosing, confidence intervals of the estimated poverty rates. I focus more on this in chapter 4; here I briefly point out the ignored uncertainty contained in the PPP estimates. As discussed above the PPP exchange rates are hardly a set of uncontested figures. And this observation gains in importance when one uses such PPP rates for poverty estimates due to the methodological mismatches already mentioned.

The ICP PPP rounds do not report any confidence intervals of their PPP rates.<sup>86</sup> In addition, by the construction of the PPP rates, any measurement errors in one country have an impact in the PPP estimate of all other countries. In that sense those errors are contagious, since they influence the entire series of poverty estimates for one specific country, and to a certain extend all the other countries as well. The size of those error terms is not marginal. For example, Deaton and Heston (2010) argues that the PPP estimates between China and USA contain a 25% error margin.

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<sup>85</sup>This interestingly translates to that, given the domestic real growth level in consumption, the MDG1 goal remains linked to the CPI application, and PPPs play a rather secondary and indirect role. The PPP role in trends could be attributed to shifting the level of iPL that may point it to a section of the domestic consumption distribution that may well differ in its steepness.

<sup>86</sup>Without the underlying ICP data only rough approximations can be made by independent scholars (Deaton and Dupriez, 2011b; Deaton, 2012).

Along these lines, Deaton (2001, p.129) argues that since world primary commodity prices are “notoriously volatile”, while at the same time there are some countries for which those commodities consist a large part of their GDP, PPP exchange rates can vary considerably based on the world price of those commodities in the base year of the ICP round.<sup>87</sup> He further argues that this may explain the sensitivity of the African and Latin American with every other round of PPP estimates. This indicates the uncertainty and the volatility behind PPP estimates, or their use in years outside of the base year.

Deaton and Dupriez (2009) tabulate their “PPP for the poor estimates” (P4), and estimate the level of uncertainty between various reasonable choices of iPLs and P4 estimates. However, even if uncertainties from the use of various index numbers are considered by Deaton and Dupriez, no price measurement error, or an error capturing misrepresentation of the populations is included in their approach (ibid, p.40).<sup>88</sup>

Finally, Ravallion (1994b) investigates the impact of PPP measurement errors in the poverty ranking of countries. He shows that when those errors are identically distributed in each country then it can be shown that these errors do not affect the rankings. However, if the errors are heterogeneously distributed between countries then these rankings are not a priori robust to those PPP measurement errors.

## 2.2.2 Methodological problems in estimating a dollarized poverty line

For investigating the issue of poverty in economic terms one is typically bound to use a monetary yardstick with which to distinguish the poor from the remaining population.<sup>89</sup> The flagship of iPLs is the methodology used by The World Bank and its researchers, deriving the famous dollar-a-day poverty line. This section dissects all the steps involved in the original RDV methodology and its RCS update.<sup>90</sup> In the reading of this literature that follows, I argue that the application of the dollar-a-day (hereafter also DAD) method in the global poverty literature entails a principal source of concern.

### The dollar-a-day method

The RDV framework builds on the premise that national poverty lines consist of two components. One absolute, fixed in all countries, and one relative component

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<sup>87</sup>Deaton offers the example of Nigeria whose PPP would be sensitive to the world price for oil.

<sup>88</sup>See chapter 4 for an empirical investigation of the impact of those uncertainties in global poverty estimates.

<sup>89</sup>For a promising alternative see Anderson et al. (2014).

<sup>90</sup>Reminder: RDV stands for Ravallion et al. (1991a), and RCS for Ravallion et al. (2009).



connected with the income or consumption level in each country. This relationship in RDV is expressed as follows:

$$\ln(z_i) = \beta_0 + \beta_1 c_i + \beta_2 c_i^2 + \epsilon_i, \quad i \in [\text{set of countries}] \quad (2.1)$$

where  $z_i$  is the poverty line of country  $i$ , and  $c_i$  is the average consumption in that same country. The obvious concern with this formula, as already pointed by Srinivasan (2010), is that the absolute minimum poverty line implied obtains for 0 (zero) mean consumption. Therefore the theoretical foundation of this model is limited, although the fit of the regression is fine ( $R^2 = .9$  for the small sample of 33 countries). Their model predicts a \$0.76-a-day line (95% Confidence Interval: 0.49,0.84) as a point estimate of absolute poverty line, but the eyeballing approach was found by the authors preferable to the model<sup>91</sup> giving a 1.02\$a-day (95% CI: 0.92, 1.29) for a group of poor countries that appear to cluster around the dollar-a-day level. Allen (2013) revisited the RDV data set and finds that many of the World Bank's reports for those poverty lines were either unavailable, or not enough information was provided in order to be useful for an independent assessment. In several counts, from the reports that were available, as Allen finds, several of the NPLs in the data were set in a more or less arbitrary manner, such as the cases of Pakistan and China.<sup>92</sup>

Responding to the criticism about obtaining the absolute poverty line at the level of 0 consumption, Chen and Ravallion (2001) redefined the formula in a way that tries to address this point. This is done in a rather technical manner, without providing any further theoretical support:

$$\ln(z_i) = \beta_0 + \beta_1(c_i - c_{min}) + \beta_2(c_i - c_{min})^2 + \epsilon_i, \quad i \in [\text{set of countries}] \quad (2.2)$$

where  $c_{min}$  represents the minimum mean consumption in the set of countries. This method gave an estimate of \$1.05-a-day (95% CI: 0.88, 1.24), but the median of the ten poorer countries of \$1.08-a-day (95% CI: undisclosed/not estimated) was given preference on defining the 1993 PPP based poverty line (same sample

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<sup>91</sup>As characterized in a followup publication by Ravallion (2010a, p.89): "The 1990 WDR \$1 a day line had been picked by eyeballing the scatter of points in the relationship between national poverty lines and national mean consumption"

<sup>92</sup>Similarly, for a large group of these NPLs, although the World Bank was been involved in their construction in cooperation with local authorities, there is no investigation of the actual composition of the each NPL. All that is reported in a followup article (Chen and Ravallion, 2010) is that about 80% of the NPLs use a version of the "cost of basic needs" approach, having a country specific food component and some allowance for non-food expenditure. Not exploiting this information appears rather sub-optimal.

of countries as in RDV). Ravallion et al. (2009) recast their previous econometric approach, and take on a different specification:

$$z_i = z^* I_i + f(C_i)(1 - I_i) + \epsilon_i, \quad i \in [\text{set of countries}] \quad (2.3)$$

where  $z^*$  is the mean NPL of the countries in their sample with mean consumption less than \$60-a-month (dubbed “the reference group”),  $I_i$  takes the value of 1 if country  $i$  belongs to the reference group and zero otherwise, and  $f(C_i) \equiv E[z|c = c_i]$ , while  $E[\epsilon_i|c = c_i] = 0$ . To be able to identify the methodological continuity one has to visit the working paper version in Ravallion et al. (2008, table 1), where the  $f(C_i)$  is identified fully. Their preferred specification is the linear one,  $z_i = \beta_0 + \beta_1 c_i + \epsilon_i$ , without reporting most of the typical regression results of the other specifications. Again the criticism that their methodology implies that average poverty line obtains at mean consumption 0, remains valid, although this takes place in a background formula. Nevertheless, what all this empirical jargon says is that the iPL is taken to be the average of NPL of the countries in their sample with mean consumption less than \$60-a-month from the 74 NPL data set the authors used.<sup>93</sup> This econometric approach despite its elegance, is difficult to interpret as a sufficient theoretical and methodological framework able to isolate the absolute from the relative component within each NPL (which is what the foundation of this methodological tradition –initially stated in Ravallion et al. (1991a)– aims at doing).

The iPL estimate of Ravallion et al. (2009) is \$1.25-a-day, however the confidence intervals are not reported.<sup>94</sup> As Pogge (2013) points out, this average obtains from a group of the “fifteen poorest countries, thirteen of which are small states in Africa”, along with Nepal and Tajikistan, rendering the iPL substantially SSA-oriented.

As before, RCS provide no detailed discussion concerning what were the underlying goals in terms of living standards considered in each NPL within their data set; or what methodological problems were addressed, and how, before the final figure of each NPL was estimated. Thus the authors consider each NPL of equal quality, and taken at face value, and an opportunity to dissect the NPLs in search for the absolute poverty component remained unexploited.<sup>95</sup>

Most recently, Ferreira et al. (2016) re-use the group of countries selected by

<sup>93</sup>See chapter 4 on the details of how this consumption threshold is set.

<sup>94</sup>Assuming normality one gets a 95% confidence interval of (0.48, 2.01) from the Ravallion et al. (2008) data. For a detailed estimation of the DAD poverty line and global poverty rates confidence intervals in 2011 PPPs see chapter 4.

<sup>95</sup>A detailed investigation of NPLs composition, could substantiate the absolute and relative components decomposition approach in favor of their approach; or it could lead to empirically refute the assumption that the absolute poverty component is fixed for every country.

Ravallion et al. (2009) and estimate the present day official value for the World Bank DAD iPL poverty line at \$1.9/day.<sup>96</sup> Therefore, by implication, the current iPL preserves the aforementioned methodological issues.

### **The averaging nature of iPL**

Considering that the goal of the DAD method is the estimation of an iPL that traces absolute poverty globally, there is another issue to touch upon. To this end, the dollar-a-day method implicitly assumes that all NPLs of countries in the reference group either: (1) contain no relative component, or (2) the relative component within the group of reference countries has an average of zero.

The first assumption if true it would in all likelihood falsify the underlying premise according to which the absolute component in the NPLs is fixed across all countries,<sup>97</sup> simply because the values of the NPLs vary considerably in the reference group.<sup>98</sup> Naturally, some variation should be allowed to account for the various measurement errors in the estimation procedure of each NPL, but one should not simply assume that their average would cancel out measurement error as those underlying poverty lines are not created with the same goals in mind, and therefore they are not expected to measure the same definition of poverty. If that was the case then one would be excused, in that regard, to take the average in pursue of the mean value of a international poverty line, similarly to the repeated lab results of a experiment designed to measure exactly the same phenomenon.

The second assumption cannot hold outside of a rather unique coincidental arrangement of values. Thus, the joint result of these assumptions brings the methodological underpinnings of the RDV & RCS methodology to contradiction, and it does not follow that the absolute component of the NPLs is necessarily identified at any step of the process, despite that being the penultimate methodological goal.

Overall, two main concerns stem out of this averaging step taken in the RCS approach. First, the iPL as derived is more appropriate for some countries, and less for others.<sup>99</sup> And second, the exclusion of the confidence intervals from the analysis paints a beautifying picture in terms of how well this method defines the levels of the global poverty rate.<sup>100</sup>

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<sup>96</sup>See below for additional information, as well as chapters 3 & 4 that discuss this article in detail.

<sup>97</sup>Another way of seeing this is that if this assumption was well founded it could become the fixed point around which to adjust the PPP rates so that all absolute components in NPLs among all countries were equal in those new "PPP for the absolute poor" terms.

<sup>98</sup>See table A-1 in Ravallion et al. (2009) and table 6 in Ferreira et al. (2015) for their exact values (in 2005 and 2011 PPPs respectively).

<sup>99</sup>As implied by Pogge (2013), and by Ravallion and Chen (1997) as well.

<sup>100</sup>Again, chapter 4 deals with the estimation of the error terms at length. Keep in mind the substantial confidence interval from the initial estimation of the DAD value by Ravallion et al. (1991a)

The following thought experiment is helpful in clarifying the first point. Imagine in a future year, rather far from today, that all countries in the world are at least middle income countries, and no poor developing countries exist any more. If one applies this method then what it will capture would be an average poverty line of group of the least rich countries. This poverty line would, by and large, be dictated by the relative component of those NPLs. Therefore, even if one agrees that at present this method delivers an iPL that captures properly absolute poverty, as a product of time the RDV & RCS methodology would not be able to predict an absolute poverty line due to the evermore rare existence of countries with NPLs that track absolute poverty.

The same conclusion is corroborated by Ravallion et al.'s observation that with higher income the poverty line increases as well. From this one can conclude that as the poor countries grow the poverty lines will rise as well and the methodology applied by the authors will no longer be able to capture an absolute poverty level. Therefore the possibility that the methodology may produce absolute poverty lines is not an essential part of it, but is based on circumstances. This implies that the dollar-a-day method is essentially a mixed absolute and relative one. Thereby, giving more substance to the argument posed by Srinivasan (2010, p.149), that the dollar-a-day approach entails a "varying notion of absolute poverty".

Moreover, the general concern regarding the fixity of any absolute poverty notion has been discussed in Ravallion (2010a) where it is mentioned that "[b]y treating absolutely poor people similarly to relatively poor people [...] the resulting measures would lose meaning as measures of absolute poverty". This is precisely the problem with the averaging nature of the dollar-a-day approach, that for some countries the iPL would correspond to a rather relative poverty line, and for others to an absolute.<sup>101</sup> By how much it is absolute or relative for each country it is not clear without a detailed decomposition of the NPLs. However having countries with NPL smaller than the iPL arguably shows that those countries, and the residents of those countries, are not treated as the others in the developing world.<sup>102</sup> It could not be convincingly argued, in an attempt to defend the RDV & RCS method, that those countries have failed to define NPLs that meet the absolute poverty requirement, since if that was the case, those NPLs should have been dropped from the analysis in RDV & RCS, as failing to meet the basic assumptions of their methodology since each NPL is at least absolute *plus* some relative part.<sup>103</sup>

mentioned above. The estimates in chapter 4 are similar to the size of that.

<sup>101</sup> See figure 3.4 in chapter 3 for some results corroborating this argument.

<sup>102</sup> Unless one assumes that all deviations from iPL are due to measurement error (as the DAD literature does). Such an assumption would be a rather strong one on its own.

<sup>103</sup> Again an assumption that would attribute all deviations to measurement error would be necessary to support the dollar-a-day approach. Such an assumption would require some at least some indications that would convince an observer that it should be in principle considered.

Turning now to the second of the main concerns related with the averaging nature of DAD: using a single one-size-fits-all iPL, and with the particular derivation of the dollar-a-day poverty line, we are bound to cope with large degree of uncertainty. This uncertainty stems from two issues. First, from the loose representation of the absolute poverty component in the NPL of each country, and its unknown variation. And second, from the uncertainty implied by confidence intervals of the iPL estimate as mentioned above. Given the relatively high density of around the poverty line,<sup>104</sup> this results into large variation in poverty rate estimates. This last type of uncertainty is amplified if one considers the issues around the estimation procedure of PPP rates.<sup>105</sup>

An important implication of the above is pointed out by Deaton (2010b, p.12). He demonstrates how India has become “poorer”, when measured with the iPL, exactly because it had less poor people. As a product of growth in India, the country is not in the reference group of countries that is used to estimate the iPL. However the NPL of India is lower than the latest iPL. Excluding India from the group of countries that define the iPL, implies an important *discontinuity* for the poverty estimates in this country. Finally, it is not obvious or clear why RDV & RCS choose a country level average, and not a population average of the countries in their reference groups. Or why they do not follow within their framework the suggestion of Deaton to use all the NPLs in their dataset and weigh them with population to derive the iPL. This would be perhaps more reasonable within their framework of pin pointing the most typical PL for the average poor *individual*, but instead Ravallion et al., and more recently Ferreira et al. (2016), average as if they are interested for the average poor *country*.

### 2.3. Household Surveys: Consumption and Income Based

Household Surveys (HHS) provide indispensable information about the distribution of economic resources among the economic units of interest, such as individuals or households. HHS tend to either focus on measuring income or consumption, and despite the general agreement that consumption based HHS are preferable to income (when both are available), some authors are favorable in giving preference to income HHS instead (e.g. Sala-i Martin (2006)). It is instructional to shortly navigate through the various methodological flavors underlying these statistical exercises. Among HHS, one can distinguish four dimensions at the highest level: the

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<sup>104</sup>Meaning that a small change in the value of the poverty line would change more than proportionally the corresponding poverty rate.

<sup>105</sup>As mentioned above, Deaton (2012) argues that 2005 PPPs for China contain a 25% error margin. For a calculation of the iPLs CI in 2011 PPPs see chapter 4, and for a discussion of the World Bank’s approach to the issue of error terms see Moatsos (2018b).

welfare concept, the income sharing units, the unit of analysis and the equivalence scale.

The welfare concept deals with the main variable of interest for which we try to estimate its distribution. Typically the "welfare concept" is that of income, consumption or expenditure. Income based HHS typically refer to the yearly income obtained by the reference income share unit observed.<sup>106</sup> Consumption refers to the monetary value of the actual goods and services consumed.<sup>107</sup> Typically in this case there must be a "strong indication" that the use value of durable goods is used in the HHS instead of their purchase value. When purchase value is used for durable goods then the welfare concept is that of expenditure. When durable goods (and ceremonial expenses) are excluded, then we obtain net consumption; and gross consumption when included (Chaudhuri and Ravallion, 1994, p.378). Bear in mind that one of the main sources of distributions UNU-WIDER (2014, p.6) issues a warning that some items are "badly covered", and occasionally it is not clear if in-kind incomes are included or not.

The second dimension in which HHS may differ is the "sharing unit" used. Sharing units can be households, tax units, or persons. A household in this case is broadly defined as covering those people who share the same dwelling, although it can also take a stricter definition when the dwelling and the other resources are shared. A tax unit follows the legal definition in each country-year combination and can vary accordingly. Finally, the income sharing unit is that of a person and the data collection is done at the individual level.

The third dimension is the "unit of analysis" which can be either the household or the person. It is the household when the size and the within household heterogeneity is not taken into account, or it can be the person when these same household aspects are taken into account (UNU-WIDER, 2014, p.7). It is understandable that the distribution can look substantially different when the unit of analysis is at the level of the household or when it is at the level of the individual.

Finally, the fourth dimension is the "equivalence scale". The "equivalence scales" are conversion methods that attempt to correct for the heterogeneity across households, in terms of size and composition. For example, if such heterogeneities

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<sup>106</sup>The income related welfare concepts in the World Income Inequality Dataset (UNU-WIDER, 2014, p.6) can be further distinguished in: Market income that includes employee income, income from self-employment and property income. Earnings income that includes only employee and self-employment income (net or gross). Gross income which is the market income above, where social transfers are added. Monetary gross income obtains from gross income when one excludes the in-kind incomes, imputed rents and home production. Taxable income obtains from monetary gross income if one considers the various exemptions. Monetary disposable income is then calculated from monetary gross income by subtracting relevant taxes. From the aforementioned definition of gross income deducting the taxes and social contributions gives the disposable income.

<sup>107</sup>Note that fines and taxes should not be included here.

are generally ignored it is as if one assumes that a single person household having the same total income (or consumption) with a four-person household both enjoy the same welfare level. Arguably it is hard to defend such an assumption. At the same time one needs to correct for economies of scale (for example, it is very reasonable to assume that typically with the same heating expenses more than one persons can be warmed). There is a variety of methods to do so, using the actual household size or its square root, or more generally a function using the number of the adults and children in the household.<sup>108</sup> On this issue however, Dhongde and Minoiu (2011) warns that in global poverty measurement household level consumption data are converted to per capita "simply by dividing total consumption by the number of household members, ignoring economies of scale in consumption or inequality in the intra-household allocation of resources".<sup>109</sup> Chen et al. (1994, p366) notes that "[t]he per capita normalization implicitly makes the quite special assumption that each person (whatever their age or gender, or how many other people live in the household) should have the same weight."<sup>110</sup>

In addition, HHS may differ with respect to their population, or geographical, coverage. For example, the focus of a survey can be urban or rural, or ideally in respect to the estimation of poverty, cover the entire population and areas. However, even for surveys that aim at covering the entire population, institutionalized individuals (e.g. pension houses, or prisons) are typically excluded from the survey by design. At the same time though some individuals are, directly or indirectly, opting out of the survey. For example, individuals that refuse to partake, or those living in gated communities where the survey conductors rarely gain access to.

Generally, not all income is consumed, and inversely not all consumption is a portion of one year's income, as inter-temporal consumption smoothing may occur.<sup>111</sup> Therefore, income that the household obtains within a particular time period, typically a year, can be thought of only as a proxy for actual consumption. On this point, Deaton (2001, p.142-3) identifies that between years "measured consumption is famously less variable than measured income". Lopez and Servén (2006) investigate the log-normal assumption on consumption based distributions

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<sup>108</sup>For example the OECD equivalence scale: "assigns a value of 1 to the first household member, of 0.7 to each additional adult and of 0.5 to each child", also called "Oxford scale".

<sup>109</sup>As noted in Dhongde and Minoiu (2011): Haddad and Kanbur (1990) and Székely et al. (2004) provide further discussion on the issues of equivalence scales and of within household resource allocations.

<sup>110</sup>For arguments in support and against this assumption see Ravallion (1994a).

<sup>111</sup>An important issue arises here, since one may consider that saved income is also part of consumption, if one things that saving is a "good" or "service" in itself. Chen and Ravallion (2010) remind us about "(long-standing) concern where economic welfare measured by income encapsulates a double counting as a product of time: saving (or investment) is counted initially in income and then again when one receives the returns from that saving."

and conclude that it is “unambiguously” rejected, and attribute this finding to a smoothing effect present in consumption distribution.<sup>112</sup> Deaton (ibid) expresses his preference in the use of consumption over income surveys, wherever available, while criticizing techniques followed at the time by Chen and Ravallion (2000) where by using NAS they “converted” income based distributions to consumption. The result of this conversion, Deaton argues, is poor in its capacity to estimate poverty.

Chen and Ravallion (2004) give preference to consumption based distributions in their estimations for global poverty. In response to the aforementioned methodological critique by Deaton, they test the 27 countries at their disposal, for which they have both income and consumption based distributions, to see if the difference in the population weighted average poverty is statistically significant or not. They conclude that it is not for the \$1 dollar or the \$2 dollar a day line (in 1993 PPPs).<sup>113</sup>

At the same time Deaton and Zaidi (2002), offer some practical considerations about why one prefers consumption over income, in developing countries where small businesses and agriculture are the norm. In such economic environments, where people are mostly self-employed it is “notoriously” difficult to measure income accurately. Income considerations such as depreciation of tools or animals usually rest on a “host of assumptions”, which in turn give rise to further reservations about the accurate measurement of the income variable. An advantage of the consumption based surveys, according to Deaton and Zaidi (ibid), is that the concepts involved are more clear, and the required protocols to be observed are “well-understood”, while less imputations is needed. Overall, the consensus is that consumption is “less understated” than income, although it is still expected to be understated from its actual value in the overall distribution (World Bank, 2014, p.18).

## 2.4. NAS vs HHS: Which is the most appropriate mean?

The selection of NAS vs HHS estimation of distributions’ mean in estimating global poverty provides perhaps the most firm dichotomy in the literature, while also entailing large differences in trends and levels in the results that those two

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<sup>112</sup>The assumption of log-normality for income distributions builds on the theoretical work from Aitchison and Brown (1957, p.111-115) who show how to invert a Gini index and obtain an entire distribution based on the functional form of the log-normal distribution. For a more detailed discussion of the log-normal assumption see chapter 5.

<sup>113</sup>At \$1 a day the poverty rates is 17.8% for consumption and 21.2% for income, and based on a t-test they find no statistical significance in this difference ( $t = 0.73$ ;  $n=27$ ). At \$2 a day, they report a 48.2% rate for consumption and 44.8% for income, also not significant ( $t = 0.49$ ). In any case, thereafter, the authors decide to abandon their practice of “converting” income distributions to consumption ones.



options entail. As Pinkovskiy and Sala-i Martin (2016) put it "researchers using household surveys find much higher poverty and much slower poverty declines than do researchers using national accounts", alluding to the importance of this methodological decision.<sup>114</sup> Most importantly the difference between NAS and HHS captured income or consumption is not just in levels, but there is a substantial divergence among the growth rates as well (Ravallion, 2000).

Ravallion (*ibid*) reports that for India along 11 HHS rounds in the 80s and 90s the average growth rate in consumption for HHS is  $0.75 \pm 0.19$ , while for NAS this is  $2.56 \pm 0.14$ . Deaton (2010a) using a sample of 88 countries, covering the years from 1987 and 1998, finds that the annual growth rate of the HHS mean consumption was 0.90%, while the NAS real per capita consumption growth rate was 3.3%.<sup>115</sup> These findings make Thorbecke (2011) to conclude that: "[n]o wonder that studies anchoring income distributions on the latter yield rosier pictures of progress in the fight against poverty than the former." Deaton (2010a, p.217) concludes that only HHS allow us to measure poverty, and that "the NAS is more likely to capture larger transactions than smaller ones, which is close to the opposite of what happens in the surveys, where large transactors are the least likely to be included" (p.219, *ibid*).

Deaton (2003b), despite acknowledging that as a standard the national income and product accounts (NIPA) command a wider recognition across countries compared to HHS design, he argues that this in turn does not necessarily mean that NIPA data are more accurate relative to those from HHS.<sup>116</sup> Deaton further recognizes a number of components included in the NIPA standard for measuring consumption, but not in the HHS<sup>117</sup> and vice versa<sup>118</sup>, which implies that the under-

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<sup>114</sup>Clearly this is no place for a detailed exposition with the issues related to the methodology applied in Pinkovskiy and Sala-i Martin (*ibid*) work, but to put it succinctly the authors seem not to distinguish recognizably between economic activity and individual welfare, which stands as the main conceptual issue of this paper. Arguably poverty is more directly linked to the latter than the former. At the same time the correction they apply is distribution neutral, which does not seem to be corroborated by available evidence (on this point see also Ravallion (2000) and on the link between economic activity and satellite night-light imagery –which is used by Pinkovskiy and Sala-i Martin (*ibid*) –consult Bickenbach et al. (2013)).

<sup>115</sup>The NAS consumption component is typically dubbed "private final consumption expenditure" (PFCE), or "household final consumption expenditure" (HFCE).

<sup>116</sup>For example, Pinkovskiy and Sala-i Martin (2016) cite the work of Johnson et al. (2013) who find evidence suggesting that in developing countries GDP per capita measurement error could be as high as 30%.

<sup>117</sup>Missing elements from HHS include: "consumption in the form of imputed rents of owner occupied housing"; "consumption in the form of imputed charges for financial intermediation"; "consumption by non-profits; residual business consumption"; "incomes from employer's contributions to pension funds".

<sup>118</sup>Missing elements from NAS include: "the component of annuity incomes that represents run-down of assets, as opposed to income"

lying concept differs between the two data sources.<sup>119</sup> Deaton (2010a) analyzing these fundamental differences points out that surveys "are probably better at picking up consumption from informal-sector activities". Chen and Ravallion (2004) argue that part of the difference in the growth rates between these two sources may be attributable to the growth of non-profit organizations' spending, which is not part of the HHS concept, but it is being captured in the NAS. At the same time, due to the method used in NAS to estimate consumption, this component cannot be distinguished from household consumption (Ravallion, 2003b).

Ravallion (2003a, p.12) further investigates this point with respect to the estimation method for consumption used in the NAS that can be characterized essentially as "residual claimants".<sup>120</sup> Which basically means that the consumption component in the NAS is not a direct estimate, but it is estimated as a residual when all other components of GDP have been subtracted. This has the natural consequence that "it lumps the errors in all other components together, with no reason to think that they cancel out" (Ravallion, *ibid*). Sundaram and Tendulkar (2003) also warn about the wider definition of consumption in NAS and about the nature of its indirect estimate.

Overall, the informed opinion of Chen and Ravallion (2010) is that considering the actual estimation of NAS consumption component "in most low-income countries, we would be loath to assume it is more accurate than a well-designed survey". Deaton and Heston (2010, p.5) agree on this point, since NAS in "many low-income countries remain very weak, with procedures that have sometimes not been updated for decades" and that "[i]n many cases, the prices collected under the auspices of the ICP may be more accurate than the GDP numbers". Further on this point, and with respect to the statistical quality of GDP in Africa, Frankema and van Waijenburg (2012) put forward the work of Jerven (2013) who shows that for a wide range of reasons several Sub-Saharan Africa GDP estimates are biased and error prone. The reasons Jerven offers span from "lack of capacity at statistical offices (to cover the informal sector), from political incentives to bias estimates upward (to show nice growth rates) or downwards (to remain eligible for international aid)" all the way to "inaccurate population censuses in response to tax threats (downward bias) or the prospect of subsidies related to village or household size (upward bias)" (Frankema and van Waijenburg, 2012, p.899, fn.13).

Some researchers, such as Bhalla (2002a) and Sala-i Martin (2006), apply a uniform multiplier that shifts the HHS distribution up to a value obtained by NAS.

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<sup>119</sup>Ravallion (2003a, p.12) also points out to Bhalla's comment that "these differences are well recognized and can be easily removed to obtain NAS estimates of household consumption". However, any careful reader of Bhalla's book, and here Ravallion as well, can make the trivial observation that Bhalla does not actually remove those mismatching components from the NAS measurements.

<sup>120</sup>A term coined by Ruggles and Ruggles (1986)

On this point Pinkovskiy and Sala-i Martin (2016) form the opinion that “survey nonresponse is unlikely to be independent of respondent income”, therefore the higher the income the higher the propensity to dodge the HHS interviewer or to reveal their true incomes or consumption. Korinek et al. (2006) gather evidence suggesting that the affluent individuals in United States are almost 50% less likely to respond to an HHS than the those living in conditions of poverty, and that indeed compliance falls monotonically with income. This is a follow-up from a similar investigation for India by Ravallion (2000) where although the author acknowledges the possibility that actual HHS data underestimate consumption growth, he cannot identify an “obvious reason” why such a gap would be distribution neutral. In the same spirit, Deaton (2010a, p.219) argues that simply ignoring the possibility of a distributionally non-neutral gap in consumption growth “assumes that these items are distributed between poor and non-poor in the same way as are the goods measured in the survey, an assumption that is not true.”

Sundaram and Tendulkar (2003) find that for the bulk of items (75%) which are typically consumed by the poor, the divergence between the NAS and HHS estimates was relatively small, even negative occasionally. They conclude that simply applying a uniform multiplier for the consumption estimated in HHS to match the NAS results in an overstatement of the consumption for those who lie at the lower 30% of the distribution. Such a "correction" as performed by Bhalla (2002a) would produce "a spurious reduction in the headcount index", as noted by Ravallion (2003a). Finally, Deaton (2010a, 220)—referring to the issues mentioned above—argues that "there is no credibility to the claim that globalization has been good for the poor based on a calculation that applies badly measured distributional shares to (upwardly biased) measures of growth from the national accounts".

## 2.5. Conclusions

This chapter discussed the nuts and bolts of the state-of-the-art in measuring global absolute poverty. The vast majority of the articles on the topic are presented in some detail. From this relatively small literature, in comparison to the vast literature on poverty per se, there are a number of points useful to rehearse here.

First, the important work done by the pioneers in the field has allowed us to have a first estimation of the levels and trends in global poverty (Ahluwalia et al., 1979; Ravallion et al., 1991a; Bourguignon and Morrisson, 2002). The growing availability of distributional information on consumption (or income) both contemporary, as well as historically, expands our ability to estimate poverty with an increased coverage of global population.

Second, the literature on global poverty measurement remains entirely focused on the rather handy measure of the dollar-a-day with limited theoretical founda-

tions. It is not clear how large the effect of the aforementioned limitations of this method is on global poverty estimates, unless we have another approach to compare it with. Such an alternative method is the cost of basic needs approach that has not been used in the global poverty literature up to this point. Key scholars of the field strongly recommend its use for global poverty measurement (Reddy and Pogge, 2010; Atkinson, 2016; Allen, 2017).

Third, using consumption based HHS is methodologically more appropriate for the estimation of poverty for a number of reasons discussed above, and income based HHS should only be used when the former are not available. National Account Statistics should not be used as a substitute of data already available in HHS, such as the mean of the distribution. Doing so may account for some of the issues related to the available (and naturally imperfect) HHS, but introduce other biases which may be the source of larger concerns.

Fourth, the findings in the literature indicate a reduction of poverty in the recent years, particularly due to the economic growth of China. Depending on how exactly each researcher measures global poverty the exact levels and trends differ; at times substantially. The main elements at play that define the level, but also the trend, are the value of the poverty line and the choice between using the HHS mean values or substituting them with an NAS statistic. HHS show slower progress and higher levels of poverty, while the use of NAS statistics show faster reduction and lower levels of poverty at the present. At the same time the higher the international poverty line used in PPP terms –mechanically– translates to an increase in poverty levels, but also lower progress made (slower reduction).

Fifth, the unrecommended habit of not reporting (or perhaps not even estimating) the uncertainty of global poverty estimates, should be avoided, and methods for accounting the impact of all sources of uncertainty in those estimates should be developed (Atkinson, 2016).

In sum, the literature on global absolute poverty has largely stagnated around the dollar-a-day concept, and has not evolved in its core methodological underpinnings. The proposition to replace HHS mean consumption or income with NAS data, that has been followed up by some scholars since early 2000s, forks the literature in a rather less methodologically sound strand. The fundamental and long-standing method in estimating national poverty in terms of a cost-of-basic-needs framework has not been investigated in estimating global poverty levels and trends.<sup>121</sup> The chapter that follows is the first attempt to fill this gap in the literature.

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<sup>121</sup>The invaluable contribution of Allen (2017) provides a framework for doing such an estimate, but it does not provide any global poverty estimates. The first such contribution is the one provided in chapter 3 of this thesis (Moatsos, 2017a).

## Chapter 3

# Global Absolute Poverty: Behind the Veil of Dollars

by Michail Moatsos<sup>1,2</sup>

*“However, the characteristics of the goods do not tell us what the person will be able to do with those properties.”  
Sen (1985, p.6)*

The widely applied “dollar-a-day” methodology identifies global absolute poverty as declining precipitously since the early 80’s throughout the developing world. The methodological underpinnings of the “dollar-a-day” approach have

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been questioned in terms of adequately representing equivalent welfare conditions in different countries and years. These key issues of measuring global poverty are addressed here using the concept of the bare bones consumption basket (BBB). This methodology pinpoints equivalent levels of welfare, both internationally and intertemporally. The results validate the critique against the “dollar-a-day” methodology, showing large variations in costs of BBB between countries and years, even when one explicitly allows for additional expenses such as education and health. This volatility represents the differential among the typically used average CPI and a price index which is more relevant to those living in absolute poverty. On a point estimate level, success in terms of the first Millennium Development Goal (MDG) appears marginal. Once uncertainty in the estimates is accounted for, the BBB poverty lines provide the ground to dispute MDG 1 early celebrations. While BBB absolute poverty remains at very low levels during the entire 1983-2014 period, it also demonstrates strong persistence throughout. On the contrary, the higher welfare level BBB derivative shows overall much less flattering poverty levels.

### 3.1. Introduction

The state of the art in the global absolute poverty literature is encapsulated in the World Bank’s PovcalNet estimates. The “dollar-a-day” methodology endorsed therein has prevailed as the field’s standard for several decades now. Those estimates show that absolute poverty throughout the developing world was in the vicinity of 50% during the early eighties, then dropped to about 35% by the second half of the 90’s, and by 2012 it was about 15%.<sup>3</sup> This constitutes a more than three-fold reduction in about 30 years. Taken at face value this translates to an enormous success on poverty reduction on a global scale. However, reliable estimates and conclusions can only be the result of a well founded methodology. The lack of convincing methodological underpinnings has been the principal concern in the long list of critics throughout the literature (Reddy and Pogge, 2010; Deaton, 2010a; Srinivasan, 2010; Aten and Heston, 2010; Subramanian, 2015; Moatsos, 2015). Those voiced concerns boil down to the issue of intertemporal and international consistency in measuring absolute poverty. The fundamental issue resides with the extent to which any monetarily fixed iPL is capable of measuring absolute poverty with the same standard all over the world and over time.<sup>4</sup> If empirically

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<sup>3</sup>For reasons of comparability we keep the same definition of developing countries as the World Bank does. That is if the country was categorized by the World Bank as developing in 2005 then it remains categorized as such for the entire period (1983-2014).

<sup>4</sup>Recently the World Bank has commissioned in June 2015 a group of scholars to update the global absolute poverty methodology. The issue of holding the global poverty yardstick constant in real terms is one of the two commission’s main tasks. The present paper closely follows recommen-

substantiated, such criticism directly questions the validity of the “dollar-a-day” methodology since in international poverty measurement “the first-order issue is to demand welfare consistency” (Ravallion, 2015, p.4). Without a consistent methodology of measuring global absolute poverty, investigating the effect of growth or inequality on poverty, or the result of policy on global poverty will remain perennially at bay.

The principal sources of the “dollar-a-day” inconsistency reside with the use of purchasing power parity (PPP) exchange rates, that relate with total household consumption, and consumer price index (CPI) rates tracking average consumption. On the one hand, the PPP rates are used to express the national poverty lines and the consumption distribution to international dollars adjusted for purchasing power differentials. Thus PPP rates bear the responsibility to achieve the between countries equivalence of the welfare level encapsulated in the iPL. However, this can only be performed for the benchmark year that the PPP rates are available.<sup>5</sup> On the other hand, the CPI rates are used in order to apply the iPL on years other than the PPP benchmark. Thus the CPI rates are responsible to deliver intertemporal welfare equivalence within each country. As a result, the global absolute poverty literature accepts the implicit proposition that a fixed value in PPP dollar terms represents the exact same standard of living (in conditions of absolute poverty) for all people around the world.

Nevertheless, the PPP exchange rates do not necessarily achieve this equivalence for the least affluent groups (Deaton, 2010b; Deaton and Heston, 2010, among others). In addition, the CPI rates applied are plutocratic and thus not constructed to follow the consumption of those living in poverty (Reddy and Pogge, 2010). Consequently, the central argument that is substantiated in this paper is that only by coincidence the iPL would be consistently representative of a welfare specific type of absolute poverty in any specific country, or the world as a whole.

The alternative—to the “dollar-a-day”—methodological approach is to estimate absolute poverty on a global level using appropriately defined consumption baskets for each country and year separately. Measuring poverty using a consumption basket is an approach far from novel. One of the early reference points is to Rowntree (1901) as cited in Kakwani (2003). In addition, the concept of a well defined consumption basket is found in most of the national poverty lines that the World Bank uses to derive the iPL (Chen and Ravallion, 2010, p.1584). However, the consumption basket approach has been dismissed by World Bank researchers on the basis that people living in poverty adapt their consumption habits in response to

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dition 15 in their report (Atkinson, 2016, p.xxi).

<sup>5</sup>Recently, the PPP rates are estimated by the ICP project every 6 to 8 years. The latest benchmark year is that of 2011, and it is the ICP round followed here. The results shown here hold for the 2005 ICP round as well (Moatsos, 2015).

relevant price changes (Ravallion, 2010a), and more recently as paternalistic (The World Bank, 2016).<sup>6</sup> As already noted by Allen (2013), there is no reason why this type of behavior could not be accommodated in the subsistence basket. Given the long standing foundations of the consumption basket method as such, and that the core of the necessary data is readily available from various sources, it seems rather bizarre that no one before has pursued the goal of applying such a method on a global scale.

Therefore, the contribution of this paper to global poverty measurement is the use of well defined purpose oriented consumption baskets to provide estimates of poverty levels and trends throughout the developing world. This is done for the 32-year period 1983-2014. The BBBs account for the substitution effects by the poor—that occur as a result of price fluctuations—by selecting the cheapest available nutritional sources that meet the minimum dietary energy requirements (MDER) and suffice for a reasonable amount of proteins. In light of the identified issues with the iPL methodology, the main innovation embedded in the BBB approach is that it completely avoids the use of both the PPP rates, since the calculation takes place in the local currency for each country, and the average CPI rates, since the re-estimation of its value is done from the nominal price dataset for every year separately.

Conceptually the basic version of the BBB closely observes the definition of absolute poverty by Unesco, according to which: “[a]bsolute poverty measures poverty in relation to the amount of money necessary to meet basic needs such as food, clothing, and shelter.”<sup>7</sup> For the purpose of depth in measuring global poverty, an additional BBB derivative is constructed<sup>8</sup> that follows closer the definition used in the Copenhagen Declaration by the United Nations: “[a]bsolute poverty is a condition characterized by severe deprivation of basic human needs, including food, safe drinking water, sanitation facilities, health, shelter, education and information. It depends not only on income but also on access to social services.”<sup>9</sup> In addition, the BBB derivative closely follows article 25 of the Universal Declaration of Human Rights. Pogge (2011, p.2) utilizes this article in defining an individual as living in poverty when he lacks: “a standard of living adequate for the health and well-being of himself and of his family, including food, clothing, housing and medical care.”<sup>10</sup>

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<sup>6</sup>The paternalistic argument ignores the fact that the “dollar-a-day” iPL is in practice also externally imposed to any given country, and at the same time it is lacking defensible methodological underpinnings.

<sup>7</sup>Obtained from Unesco on February 22nd, 2016.

<sup>8</sup>Introduced in section 3.2.3.

<sup>9</sup>Obtained from UN, Copenhagen Declaration on February 22nd, 2016.

<sup>10</sup>Universal Declaration of Human Rights, G.A. Res. 217 (III)A, art. 25, U.N. Doc. A/RES.217(III) (Dec. 10, 1948).



The rest of the paper is organized as follows: Section 3.2 provides a thorough exposition of the methodology applied. Section 3.3 exhibits the data and sources used, and section 3.4 positions the constructed poverty lines in comparison to the dollar-a-day line. Section 4.3 presents the new global absolute poverty estimates on regional and global levels, as well as for a small set of key countries, and in comparison to the World Bank's figures as reported in PovcalNet. Section 3.6 concludes.

## 3.2. Bare Bone Baskets

### 3.2.1 Articulating consistent poverty lines

The concept of measuring absolute poverty internationally using a common achievement has been explicitly proposed by Reddy and Pogge (2010) and implicitly by Allen (2013). To this end, Reddy and Pogge argue that any two currency amounts are equivalent in time and space only if they both just suffice to meet a common achievement. In the case of BBBs, the common achievement is bare bones survival, calculated based on choices mainly given by nature in terms of most basic nutrients absolutely necessary for survival, and largely beyond normative judgments. Furthermore, BBBs by construction observe the principle of consistency as defined in Ravallion and Bidani (1993, p.2). According to that definition, consistent poverty lines must be comparable between different regions and subgroups, thus “representing the same level of welfare”.<sup>11</sup>

Basic nutritional needs provide a widely defensible and objective starting point for consistently defining a common achievement and a common welfare level. In accordance to Sen (1980), the level of income or consumption that suffices for basic nutritional needs to avoid malnutrition “has a claim to be considered as an appropriate poverty line even when [...] nutritional requirements vary interpersonally around that average”. The satisfaction of those basic nutritional needs, along with the basic needs required by the Unesco definition, such as housing and clothing, assemble the foundations that the BBB methodology builds upon. In practice, consumption baskets are embedded in the iPL as well, albeit in an inconsistent manner. According to Chen and Ravallion (2010), 80% of the national poverty lines (NPLs) used in Ravallion et al. (2009) to derive the iPL of 1.25\$-a-day in 2005 prices, are constructed also using some variation of a cost of basic needs approach. In all its versions, the dollar-a-day iPL is estimated by averaging a set of NPLs from a group countries (Ravallion et al., 1991a; Chen and Ravallion, 2001;

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<sup>11</sup>The other principle that Ravallion and Bidani (1993) defines is that of “specificity”, which relates to poverty lines that are representative of “existing norms or values in a society” (Marivoet and De Herdt, 2013, p.2). BBBs do not necessarily observe that principle.

Ravallion et al., 2009; Ferreira et al., 2015), without any explicit analysis of what the underlying NPLs actually represent in terms of welfare.<sup>12</sup> The methodological variation among the NPLs underlying the iPL, especially with respect to the encapsulated normative choices<sup>13</sup>, does not allow for any use of the NPLs, as they stand, to consistently measure global poverty. These methodological choices in the construction of iPL are insufficient, since, in order to avoid the application of inadequate PPPs, it is necessary to have local poverty lines that have been derived using the same method on every country individually. NPLs fail to provide such a basis. Moreover, local poverty lines must be separately calculated for every year, based on domestic prices, to avoid using average consumer price indices as much as empirically possible.

Allen (2001) defines the BBBs for use in the historical real wages literature, and de Zwart et al. (2014) apply them on a global scale. Table 3.1 contains the overview, and compares with the BBB definition followed here. The main component of the basket is the consumption of staple food, and in a secondary role the consumption of beans/peas. Some minimum consumption variety is included in the basket by allowing the consumption of 3 kg of meat on a yearly basis, or 6 kg of fish if cheaper. The food component also includes 2 kg of sugar and 3 kg of butter, oil, or ghee per year. In total the food component should allow for 40 gr of protein per day and a specific number of kcal per day. The non-food component includes allowance for clothing in the form of 3 meter of linen, some candles and lamp oil, and 3 mbtu of the cheapest fuel per year. Finally, a mark-up of 5% provides the means for extremely basic housing facility. As shown in the last column of the table, the BBBs from the real wages literature are updated here in a number of ways.

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<sup>12</sup>The latest value of the iPL is set to \$1.90 in 2011 PPP by Ferreira et al. (2015) following the “dollar-a-day” methodology.

<sup>13</sup>For example, Ravallion (2015, p.4) argues about the existence of “clearly political resistance” in updating NPLs, and Kakwani (2003, p.10) offers as an example the NPL of Pakistan for not allowing a “meaningful comparison of poverty incidence in different periods” due to explicit methodological choices.

Table 3.1: Classic bare bones baskets compositions for a male adult\*

Commodity	Unit/Year	N.Europe	China	India	Africa	L.America	BBB
Main staple	kg	155-178	171-179	164-209	185-413	132-165	MDER**
Beans or peas	kg	20	20	20	-	45	MDER**
Meat or fish	kg	3 or 6	3 or 6	3 or 6	3 or 6	3 or 6	3 or 6
Butter/oil/ghee	kg	3	3	3	3	3	3
Sugar	kg	-	-	2	2	2	2
Soap	kg	1.3	1.3	-	1.3	1.3	1.3
Linen (defined)	m	3	3	3	3	3	3
Linen (applied)	share	8%	8%	8%	8%	8%	8% ± 2%
Candles	kg	1.3	1.3	-	1.3	1.3	1.3
Lamp oil	liter	1.3	1.3	-	1.3	1.3	1.3
Fuel	mbtu	3	3	-	3	3	temperature**
Cooking	mbtu	-	-	-	-	-	MDER**
Housing	mark-up	5%	5%	5%	5%	5%	5% ± 2%

*Note:* variation in the weight of the main staple represents the different staple used for different sub-regions, see de Zwart et al. (2014); Allen et al. (2011) for more details.

\*: as defined and applied for different parts of the world; adapted from de Zwart et al. (2014). Last column contains the composition of the basic BBBs adapted for measuring contemporary global absolute poverty.

\*\* : calculated as a function of Minimum Dietary Energy Requirements (MDER) or temperature as noted respectively; see text for details concerning the estimation of each component in the BBBs.

First, in both Allen and de Zwart et al., the nutritional content in kcal is fixed to 1455 kcal per person, and Allen (2013) revised it to 2100 kcal per person, as the original value was found too low. In any case, in Allen's methodology the same caloric target is set for all countries and for all years. In the context of absolute poverty, this extrapolation ignores the important variation and the changes in the anthropometric characteristics, as well as the evolution of the population's age/gender composition. For example, an increase in height, while maintaining the same relation of weight and height, would imply an increase in the number of kcal needed at minimum. In other words, if one chooses not to update the nutritional content of the basket for what the FAO calls the minimum dietary energy requirement (MDER) for each country-year, the result would be measuring poverty for a population different to what it actually is. If the MDER for a country is lower (higher) than the MDER incorporated in the calculation of the BBB value, then we will be overestimating (underestimating) actual absolute poverty. Kakwani (2003) argues that using an average calorie allowance for all "gives biased estimates of poverty incidence because all individuals do not have the same caloric needs". This argument refers to measuring poverty within a country, but it also holds on the international level. Despite the empirical challenge to account for individual differences within countries, it is relatively easy to account for the differences in minimum nutritional energy requirements between populations.

An additional consideration should be set forth in support of using MDER for determining the nutritional content of the consumption basket. The poverty lines alone cannot provide an answer for the incidence of poverty, as a distribution of a welfare measure is required as well; typically that of consumption, or income as a second best choice. These distributions are corrected for the size of the household in the sample, and the resulting distributional information is on a per-average-individual basis. In absence of such a correction there would be cases where a family of 2 with say \$20,000 income would be worse off than a family of 3 with \$20,500. Such a ranking is reasonably disputable, and a statistical correction is applied. At the same time, due to the large differences in energy requirements within the population, by different age cohorts for example, implies that "the incidence of poverty will likely be overestimated among families with children and underestimated for couples without children" (Kakwani, 2003). Which is essentially the same problem the welfare distributions face before household size correction. Given this observation, the corresponding representation of energy requirement should also be in terms of average individual basis. By construction this is what MDER represents on the population level.<sup>14</sup>

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<sup>14</sup>There might be a bias introduced by the use of MDER to the extent that the household size correction is consistently closer to the concept of adult male equivalence, than that on MDER. However, controlling for such a tentative bias requires knowledge of the underlying data which remain at bulk

More specifically, the calculation of the BBB caloric content follows FAO's (2008) methodology consisting of a set of equations that estimate the energy requirement per age/gender group based on a small set of anthropometric variables. These variables consist of the height for each age cohort, the distribution of the population by age and gender, the body mass index (BMI) that describes the relation of height and weight, and finally the Physical Activity Level (PAL) which describes the intensity of the lifestyle in terms of energy consumption. The height and BMI data are combined to get the weight for each gender/age group. Subsequently, the weight and the PAL level for each group, along with the share of each group in the total population, allow us to estimate the population wide MDER.<sup>15</sup>

The second deviation from the Allen (2001) methodology is that the food component of BBBs is restructured to move closer to the absolute minimum cost combination of resources that achieves the goal of meeting the MDER caloric intake and the 40 gr of protein per day. Thus, the main staple and the beans/peas are grouped together, and the budget minimization problem is solved via linear programming. The incorporated food variety within the BBBs is very limited even if compared, for example, to the allowance of the quite frugal 1993 NPL in India. According to Chen and Ravallion (2010), “[t]he daily food bundle comprised 400g of coarse rice and wheat and 200g of vegetables, pulses, and fruit, plus modest amounts of milk, eggs, edible oil, spices, and tea”. For an overall comparison regarding the food component, Ravallion et al. (2009) report that in NPLs the average food component share is 65% of the total costs. This share in the case of the BBBs here increases to 71% signifying the BBBs' frugality.

Lastly, the third difference with Allen's approach is that the energy and clothing allowances are linked to the year and country specific temperature conditions, thus explicitly accounting for the climatic differences between cold and warm countries. The energy allowance includes, on top of the heating costs, the energy required to cook the specific amount of calories of the BBB food component that require cooking to become edible. The energy needs related to the outside temperature conditions are calculated as the required energy to bring the temperature of a small room at 18°C, and maintain it at that level for 8 hours per day.<sup>16</sup> The temperature

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inaccessible for independent researchers.

<sup>15</sup>A distinction needs to be made in relation to the selection of BMI in different age groups. Up to the age of 10 the BMI of the median child in each age cohort is used following the FAO's model. Above that age the BMI of the 5th percentile is applied instead. This is done in order to capture the absolute minimum in terms of caloric intake for persons older than 10, without at the same time calculating such low calories for children age 10 and below that would most likely keep that cohort, and all its follow-up cohorts, shorter in the first place. Such a mistreatment would lower the population living in poverty by lowering the MDER due to the fact that the population would simply become shorter.

<sup>16</sup>The exact dimensions are 10x10x8ft.

has been chosen from the literature as a temperature above which the risk “to the health of a sedentary person, wearing suitable clothing” (Wookey et al., 2014) is minimized (see also Healy and Clinch (2002) for a further discussion). The World Health Organization also recommends 18°C as the minimum indoor temperature as noted in Collins (1986). The 8 hours duration rests on the idea that total daily hours are equally split among work, rest and leisure.<sup>17</sup> An important parameter in the calculations of the energy required for heating is that of how well insulated the room is. Since there are no readily available estimates of the exact insulation parameters, a variety of parameters representing low-cost and accessible materials is used instead. Ergo additional uncertainty in the energy requirements estimates that propagates in all the subsequent calculations. For the purpose of allocating the heating expenses per person, it is assumed that the heated room is shared by 3 to 5 persons and the heat energy produced by body heat is accordingly subtracted from the estimated required energy.<sup>18</sup> The National Oceanic and Atmospheric Organization in the USA provides monthly data for almost all developing countries<sup>19</sup>.

The clothing allowance—in lack of available prices—is estimated as a share of the basket that includes the food and energy components. This indirectly makes a link between clothing and temperature. The budget share used for imputation follows de Zwart et al. (2014) and it is set on 8%. On this a standard deviation of 2% is assumed to account for part of the variation in relative prices among countries. The energy required for cooking is estimated independently from heating energy and it is based on the FAO finding that the amount of energy needed to cook food is typically on a 3-to-1 ratio.<sup>20</sup> The aforementioned imputation assumptions are relaxed for the BBB derivative introduced in section 3.2.3

### 3.2.2 Advancing the Bare Bones Baskets as global absolute poverty lines

Given that the BBBs are estimated based on domestic prices, and that the predominant component is staple food, then by construction BBBs follow closely the variation of prices that are most relevant to those living in dire conditions of abso-

<sup>17</sup>Non workdays are treated the same as workdays assuming that social or other needs a person needs to attend to roughly replace hours normally devoted to work and take place outside of the house. An implicit assumption is that leisure takes place indoors when outside temperatures suggest it, thus pin-pointing the 8 hours per day of heating needs.

<sup>18</sup>According to FAO calculations on average for a man without an intense lifestyle the food calories converted to body heat are equivalent to a heat source of 100W; <http://www.fao.org/docrep/u2246e/u2246e02.htm> accessed on 23rd of February 2016.

<sup>19</sup>For a few countries without data the average of adjacent countries was used.

<sup>20</sup>At section 13.5 Do we really need more energy under the pot than in the pot? from “Energy for sustainable rural development projects - Vol.1: A reader” located at <http://www.fao.org/docrep/u2246e/u2246e02.htm>. Here, more cautiously, I consider a multiplier of  $2.5 \pm 0.5$ .

lute poverty. Regmi (2001), using income elasticities of demand for staple foods, finds support for this claim concluding that “the poor cannot substitute away from staple foods to anything else”. In turn, this allows for a closer monitoring of the changes for people living in absolute poverty. Such a level of granularity in measurement cannot be achieved by the “dollar-a-day” methodology, because of its lack of specificity due to its averaging nature. The “dollar-a-day” averaging occurs on three counts. First, in the way the iPL is estimated as the average of some NPLs. Second, by applying PPPs that track the household consumption on average in each country. And third, by the use of CPIs that track average consumption patterns.

Indeed the BBB method avoids this triad of problems and closely follows the common ground in the recommendations of both sides of the “how not to count the poor” argument.<sup>21</sup> On the one hand, it follows the recommendations of Ravallion (2010a), who argues that the consumption basket cannot be the same across countries due to price differences. According to this point the ideal price index should capture the price variation “of a reference level of welfare”. In the basic BBB it is the welfare level of bare bone subsistence that is being used as the explicit reference level of welfare. On the other hand, by using a reference level of welfare, it automatically incorporates the suggestion of Reddy and Pogge (2010) who conclude that only an achievement based procedure is a consistent method for estimating poverty of comparable type across countries and time. And, as already mentioned, consistency is a necessary methodological property in obtaining reliable global poverty estimates.

Lanjouw (2001) argues that “the least cost criteria rarely reflect actual consumption patterns”. And indeed, the BBBs have less to do with actual consumption patterns, and more with identifying a specific–bare bones–consumption capacity threshold. The BBB identifies the absolute poor in the world by constraining the space of consumption alternatives of any person down to the bare bone essentials. Those with consumption capacity at BBB levels, in order to make different consumption choices are bound to pay for that choice by sacrificing part of the absolute essentials, and this sacrifice has to happen in nutritional terms at large. Adopting consumption patterns that deviate the BBB does not imply that people doing so do not live in absolute poverty; they simply choose another way of surviving in absolute poverty conditions. The cost of this bare bones consumption is what the BBB tracks, thus qualifying as an absolute poverty yardstick.

In relation to the methodological inertia against applying a “cost of basic needs” (CBN) approach, such as the BBBs, Srinivasan (2010, p.145) rightfully points that any poverty consumption bundle unavoidably contains some arbitrariness. A related important objection from Srinivasan (2010, p.146), is that a common interre-

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<sup>21</sup>Referring to the article by Reddy and Pogge with the same title, and the publication exchanges thereof included in Anand et al. (2010).

gional consumption bundle is hardly representative in the presence of all sorts of geographically and cultural differences. The BBBs can partially address both of the above concerns, at least on the international level, since BBBs do not take the form of a fixed bundle, but the form of a bundle that enables a specific achievement within a cost minimizing setup. In addition, BBBs are not constructed with a particular representative household in mind, but rather the bare essentials for survival. These essentials provide enough caloric intake and prevent protein deprivation. They also—in a very frugal manner—keep a person dressed, housed, as well as not cold, and with enough fuel to cook food. This is a well-defined common achievement standard for measuring absolute poverty, that defensibly represents equivalent levels of welfare in intertemporal and international comparisons. It is also mostly linked to objective natural necessities for bare bones subsistence life conservation, thus in a lesser degree prone to arbitrariness compared to consumption baskets constructed to capture non-absolute poverty.

Another point of concern in using consumption baskets for measuring poverty can be found in Ravallion (2008b, p.6). According to this source “it is quite possible to find that the ‘richer’ sector (by the agreed metric of utility) tends to spend so much more on each calorie that it is deemed to be the ‘poorer’ sector”. This concern, does not apply to the BBBs, since by construction the cheapest—and not the minimum observed—calories are assigned to the absolute poor. Also, Ravallion (2008b, p.7) referring to the work of Wodon (1997) argues that a general increase in prices may also imply a drop in a “food energy intake”-based poverty line. In the case of BBBs this is embedded in the cost calculation process of the food component, which in nutritional terms follows the evolution of local anthropometric characteristics and is independent of actual consumption behavior.

Finally, two additional benefits are brought about with the use of BBBs in absolute poverty identification. First, as a result of the BBB method, any errors in the required data, relate only to the particular country-year a data point represents. In contrast, the chained errors in PPPs and CPIs influence the entire time-series of global absolute poverty estimation. In other words, any errors in poverty estimates are in principle not contagious to other country-year estimates. The second point relates to the underreporting of consumption -or income- in household surveys that is noted in the literature (Ravallion et al., 2007; Bhalla, 2002a; Anand and Segal, 2008). As it has been found also by Bhalla (2002a), the foodgrains, are the least understated consumption group in the 1993/4 national household survey for India. This understatement is about 10%, compared to more highly valued food products, such as dairy products, fruits, and vegetables, which show an underestimation of 53%. This observation translates in BBBs being a safer choice in hedging the poverty estimates against the household survey underreporting, since in their greater part they rely on food items that appear less prone to this problem.



### **3.2.3 Targeting a higher welfare level**

The BBBs are constructed such as to represent bare minimum absolute poverty levels in consumption terms. However, the absolute poverty yardstick can be expanded to account for other essential elements of life and wellbeing, such as education and health, as both the Copenhagen Declaration and the Universal Declaration of Human Rights stipulate. Table 3.2 offers one such BBB derivative that allows for considerably higher welfare levels compared to the basic BBB.

Table 3.2: The composition of bare bones baskets in real wages and the two derivatives applied here.

Item	Unit/Year	Real Wages Basket	BBB	BCS
Energy Target Minimization	kcal -	1455/2100 cheapest bundle	MDER	MDER mean of 3 cheapest bundles
Main staple	kg	155-413*	based on kcal/protein target**	
Beans or peas	kg	-/20/45	LP	40 at minimum
Meat or fish	kg	3 or 6	3 or 6	12 or 24
Butter or oil or ghee	kg	3	3	12
Sugar	kg	-/2	2	8
Linen (applied)	share	8%	8% ± 2%	WBGC
Lamp oil	liter	1.3	1.3	WBGC
Soap	kg	1.3	1.3	WBGC
Candles	kg	1.3	1.3	WBGC
Fuel	mbtu	3	f(T in °C)	WBGC
Cooking	mbtu	-	MDER	WBGC
Housing	mark-up	5%	5% ± 2%	WBGC
Health, Education, Water	%	-	-	WBGC
Additional shares***	%	-	-	WBGC

*Note:* The Bare bones basket with Consumption Shares (dubbed BCS) uses the average of three cheapest bundles, and four times more meat/fish, butter and sugar allowance. In addition, an allowance covering health, education, and water is included using the consumption budget shares from the World Bank Global Consumption dataset (noted as WBGC on the table). Consumption budget shares are also used for energy, housing, and clothing, and allowances for personal care, ICT, financial services, and “others” are included in the additional shares.

\*: depending on the country and main staple. \*\*: To avoid inflating the price of the consumption bundle, priority in linear programming is given to the kcal target, and protein target is allowed to overshoot by 200% at maximum if necessary. Only for Dominican Republic this cap increases the bundle price by more than 20%, and for Belarus by more than 10%, compared to allowing for unlimited protein overshooting. For all other countries there increase if any is restricted to only a few percentage points increase. \*\*\*: Additional budget shares available from the World Bank Global Consumption data include: Personal Care, ICT, Financial Services, and Others.

The BBB derivative introduced here is the Bare bones basket with Consumption Shares (BCS). In terms of the food component, it explicitly allows for 40 kg of beans or peas annually (767 gr per week), and quadruples the BBB allowance of meat or fish, of sugar and of butter, oil or ghee. The increases in meat or fish despite their size they only allow for 230 gr of meat or 460 gr of fish per week, depending which one is cheaper. Another important differentiation is that the implicit assumption according to which people living in absolute poverty have the comfort and resources to solve the minimization problem via linear programming is two-steps relaxed. Instead of the strictly cheapest staple food bundle the average of the three cheapest is used, thus expanding the variety included in the consumption bundles. In addition, explicit allowances are introduced for expenses on health, water facilities and education. Those budget shares are available by the World Bank Global Consumption dataset for about 80 countries in 2010, and on within country breakdown into four “consumption segments”.<sup>22</sup> BCS further utilizes all additional information available on budget shares from the World Bank Global Consumption dataset. Hence, all the imputation methods used in BBB are substituted by budget shares from the World Bank. Those include explicit allowances for Personal Care, ICT, Financial Services, and Other expenses.

These World Bank budget shares allow us to account for expenses about items that no global price dataset exist for. In the presence of the Engel’s law, however, they also give rise to concerns regarding the validity, consistency and comparability of the estimates across time and countries. According to the Engel’s law the higher the welfare level the lower the share a household or person will spend on food. The Engel’s law broadly holds also for international comparisons, assuming, as in the case for households, that the countries face the same relative prices. In response, the budget shares are introduced in a manner that would partially address these concerns by accounting for the implied uncertainty.

The workaround to the Engel’s law implications is to use the ratio of the estimated food-component in the BBBs over the ‘food and beverages’ budget share (FnB) of the first consumption segment. The procedure is best described in terms of an example. Suppose for instance that the BBB/FnB ratio is 0.5 for the poorest consumption group, and that the housing budget share of that group is 20%. The question is then, which is the appropriate budget share percentage to estimate the housing costs of a household consuming the BBB food component. If the housing expenses are inelastic with respect to the food expenses then the housing share should become 40% (i.e. the costs remain the same even if they increase as a share). The alternative for housing expenses would be to perfectly follow the drop of the

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<sup>22</sup>The four consumption segments are constructed following three thresholds expressed in 2005 PPP dollar terms: \$2.97, \$8.44 and \$23.03 per capita a day. For countries without WBGC data the simple average of the region was used instead.

BBB relative to the FnB, then the housing share should remain at 20%. The usual response to two alternatives is to take their average, and in this example the housing budget share would be  $30\% \pm 7\%$ , that includes half the uncertainty in the estimate as a standard deviation in order to account for our ignorance regarding the actual position of the share between the two alternatives.<sup>23</sup> For years other than 2010 the non-Food value of the BCS is updated using the average of BBB, expressed as a price index, and the CPI. This is done so in lack of an appropriate price index for the commodities and services imputed using the WBGC budget shares.<sup>24</sup>

### 3.3. Data

#### 3.3.1 Food energy

To estimate the value of the BBBs, the first step is to identify the MDER per person in a country-year following the FAO (2008) methodology. For this purpose data on the age and gender composition of the population, and the average height for adults are required, along with two basic assumptions. The first assumption concerns the height of newborns, which is set to 60% of the height of one year olds. The second concerns the Physical Activity Level (PAL) of adults, which is discussed below. The age and gender demographic data can be found at the United Nations World Population Prospects (United Nations, 2015). This dataset covers 192 countries and territories, annually from 1950 until 2015. However, the population is classified in five-year age groups (0-4, 5-9, 10-14, ..., 95-99, 100+), while the FAO model requires annual information until the 20th year, and every five years thereafter. To overcome this mismatch, a non-parametric kernel density estimator is applied to obtain the yearly approximate information on the age/gender distributions.

Regarding the PAL value, FAO (2001) offers three versions of PAL representing light, moderate and vigorous lifestyles. For working age population (here assumed to be 18 to 70), the average of moderate and vigorous lifestyles is taken as a middle-ground approach between two competing arguments: The first is in favor of a vigorous lifestyle, and assumes intense manual labor to be typical among people living in poverty. And the second argument favors a moderate lifestyle, and calls for a certain constraint in very intense physical activity due to limited nutritional sources. Thus the numeric value of PAL is set to about 2, as the average among

<sup>23</sup>In the case that the BBB/FnB ratio is above 1, the weighted average of the shares from the first two consumption groups is used. In this average, the share that has a BBB/FnB ratio closer to 1 gets the relatively higher weight.

<sup>24</sup>This approach has the advantage of by-passing the relative element introduced in the poverty identification procedure when one is yearly updating the budget shares in the presence of a differential in costs stickiness between food and non-food components as pointed in Subramanian (2010, p.34-35).

2.25 and 1.76 respectively. For the population above 70, following FAO, the PAL is set to 1.55, corresponding to the light lifestyle. Finally, a small correction of the initial MDER result is needed to account for the extra kcal required by women during pregnancy and breastfeeding following FAO (2008, p.14).

The male adult height data are from the ClioInfra (2015) height dataset, that expands the work of Baten and Blum (2012). This dataset covers 165 countries, with data starting from the mid-19th century for most. When no height information is available for any year for a given country then the average height of the corresponding region is used. The height for female is calculated using the conversion formula provided in Baten (2008).<sup>25</sup> Typically these height data are given per decade of birth and do not cover all the years we are interested in. In turn, data imputation is necessary to yearly cover the full 100-year span in each required population distribution. This was done by linear interpolation for years between the observations, and when extrapolation was needed, the regional growth rate was applied on the last observation. Sub-Saharan Africa has no data in the post-1980 period. To partially entertain concerns about this lack of data, it is instructive to observe that for the 1860-1980 period it is the region with the least volatility in height levels, and the regional average is ranging within 2.4 cm.

For modeling the growth in height up to the full adult height we use the implied growth rates from Table 3 in FAO (2008, p.8). There is, however, a mismatch on this point with the height source used. In Baten and Blum (2012) it is assumed that the full height is reached effectively during the 22nd year of age for a male person, while in FAO this happens in the 18th year.<sup>26</sup> In both cases however the same height is finally attained, the only difference is that the height growth takes more years in case of the Baten and Blum (2012) assumption. In turn, on the aggregate MDER this mismatch would play some role only if a relatively very large birth cohort is ascending from the 18th up to the 22nd year. In order to understand the implied error of this mismatch consider the case of Cambodia in 2000 which contains the relatively biggest birth cohort in the post 1983 UN WPP dataset<sup>27</sup>, the contribution of that cohort in the aggregate MDER is about 2.78% of total kcal, and we slightly underestimate a part of that.

From the height data and the body mass index (BMI) in the FAO MDER model, the weight for each age/gender group is obtained, and from the weight and the

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<sup>25</sup> male height = 28.969 + 0.8946 \* female height - 3.4242 \* NorthAfrica/SouthEastAsia, with an R-square of 0.94. The dummy for North Africa and South East Asia accounts for the fact that in those regions females are relative taller. The underlying data cover mostly late 20th century.

<sup>26</sup>More specifically, following Baten and Komlos (1998) they assume that “[t]hose who were 18 years of age were estimated to have 2.4 cm to go; those age 19 1.7 cm, those age 20 0.9 cm, those age 21 0.4, and finally those age 22 only 0.1 cm”.

<sup>27</sup>The 15-19 cohort is 2.48 times the 20-24 cohort. The average such ratio in the entire post-1983 dataset is 1.095.

FAO formulas the kcal per age/gender group is estimated. In the final step, those values are weighted by population shares of each age/gender group based on the UN WPP information. This weighted average is the MDER kcal target for a specific country-year combination. It is important to note that the obtaining kcal value corresponds to a minimum requirement because of the body mass indices used for each age/gender group. Those BMI values are selected by the FAO from the WHO reference distributions of 1995, 2006, and 2007 within the entire population. They correspond to the 50th percentile until 10 years of age, and to the 5th percentile of the distribution thereafter.<sup>28</sup>

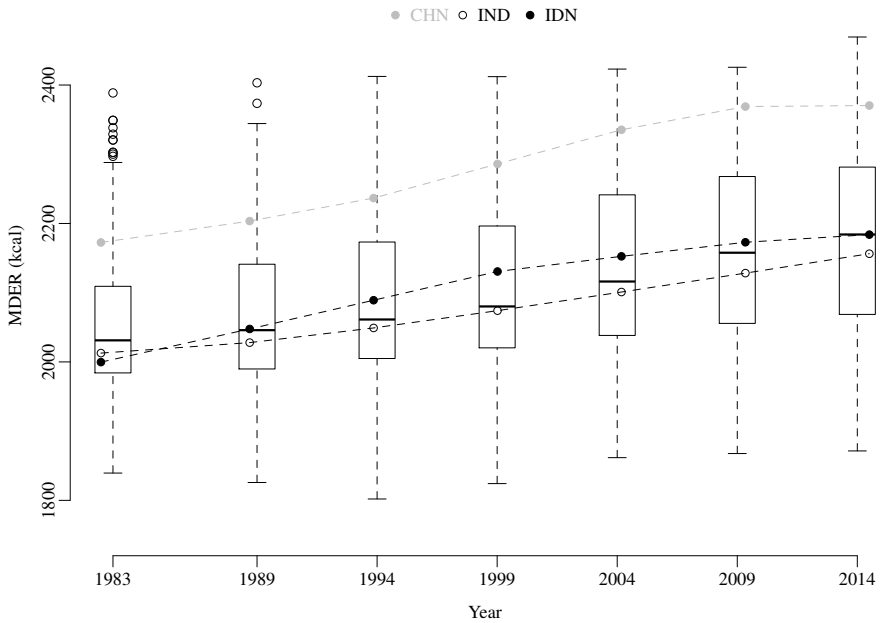


Figure 3.1: Evolution of MDER, developing countries 1983-2014

Figure 3.1 shows the evolution of the 5040 total MDER estimates for 140 developing countries, in all the years from 1983 until 2014. The median of the MDER distribution in 1983 is at 2029 kcal, with a minimum of 1839 kcal and a maximum of 2389 kcal. In 2014, the median has shifted to 2183 kcal, the minimum is at 1871 kcal and the maximum is at 2469 kcal. For China the growth in MDER from 1983

<sup>28</sup>As noted by Allen (2013) there are some typos in the formulas reported in FAO (2008). Beyond the correction he suggests, I also avoided the multiplier which doubled the energy needed for the gained weight during the first two years after birth. This was done in order to be in accordance with tables 3.1 and 3.2 in FAO (2001).

till 2014 is 9.1%, for India 7.1% and for Indonesia 9.2%. These countries are also traced on the figure in the entire period. The general trends shown in figure 3.1, demonstrate the importance of accounting in the BBBs for the changes in MDER. It turns out that keeping the caloric intake fixed to 1983 levels will introduce a median error in the caloric content of the consumption basket of 5.6%, and more than double this error for 20 countries. For 12 countries the change is on the negative side, with Niger having the larger decrease in MDER at about 2%.<sup>29</sup>

An important issue with the MDER updating is the differential among heights of the average and the least affluent groups. It is hard to be conclusive about the extent of such a differential. An indication about the prevalence of such a problem can be drawn from the evolution of heights inequality among the population. The most relevant dataset is provided by Baten and Blum (2011) through the Clio Infra website. This dataset provides Gini coefficients for a large number of countries covering most of the recent 200 years. The rationale of the investigation is that if this differential is considerable, it will be driving height inequality upwards. If one combines the evolution of heights with the evolution of inequality in heights in the post-1940 period, there is no positive trend among inequality in heights and the level of heights for developing countries. In a total of 97 pairs of height and the Gini of heights observations, 33 combine an increase in height with an increase in the Gini, while 31 with a decrease in the height Gini.<sup>30</sup>

Information regarding the nutritional content of the food items in raw form is drawn from USDA.<sup>31</sup> In addition, the loss in caloric content due to cooking has to be factored-in, as it can rise up to 40-50% for some food items. Therefore, the relevant retention rate that describes this loss is multiplied with the amount of kcal contained in the purchased form of a food item. The retention rates are provided by Appleton et al. (1999) as mentioned in Lindgren (2015).

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<sup>29</sup>The increase in MDER for India might appear as contrasting Deaton and Drèze (2009) who find a reduction of caloric consumption in India. However, this finding refers to the overall population, and they also identify an increase of caloric intake for the lower quartile in terms of consumption expenditure in the 1983-2005 period.

<sup>30</sup>Another 15 cases have a decrease in height with a decrease in the Gini, another 4 had no increase in height, and the remaining 14 cases have a decrease in height with an increase in the Gini. The overall correlation among the two is not significantly different from zero.

<sup>31</sup>Source for Nutrients Data: National Nutrient Database for Standard Reference, Release 27; accessed May 24, 2015. The three items not in USDA are: Fonio with data from here, Tortilla with data from here, and Fofou with data from here .

### 3.3.2 Food prices

With regard to the prices, the main source used is the online dataset from “The ILO October Inquiry”<sup>32</sup>, covering 222 countries and territories with prices for the period 1985-2008. The October Inquiry covers 93 items of food and drink. The data contain price information in local currency units and at the currency denomination available at each sampling year. The ILO dataset covers items that allow the pricing for most of the BBB food items, including the main staple, beans/peas, meat/fish, butter/ghee/oil, and sugar. To determine the unit costs for fuel, I used the share of each in the BBBs estimated by de Zwart et al. (2014) using pre-1983 ILO data. For fuel, when constraining to the non-extreme cases<sup>33</sup>, the cost of 1 mbtu of fuel is 4% with a standard deviation of 2%, expressed as a markup on the pre-fuel BBB cost. Additional information on prices has been gathered from FAO that covers the years 1990-2015, and WFP that covers the period 1992-2015.<sup>34</sup> All three price sources contain price information on a per market, per city or on a national level. In the first two cases I take the arithmetic average of the available prices per product. The FAO price data are in nominal terms using the most recent denomination. Thus, in order to have a homogeneous nominal dataset, I redenominated all prices back to the original denomination for each specific country-year. This was done using the dataset on history of currencies curated in the Global Financial Dataset.<sup>35</sup> For some of the most recent changes this dataset is not up-to-date, so additional sources had to be used involving information available on national central banks, along with the invaluable contribution of relevant Wikipedia entries regarding the history of some national currencies.

An important concern over prices is the differential among rural and urban prices. For India, Deaton (2003c) has estimated the urban value of his poverty line to be 11.5% higher than the rural in 1987-88, 15.6% in 1993-94 and 15.1% in 1999-2000. This information is of practical importance as it pin-points a value for this differential over a very important country for which PovcalNet provides separate distributions for the rural and urban sub-domains. This is also the case for China and Indonesia. For China, we operationalize the estimates provided by Brandt and Holz (2006) and The World Bank (2009). Those estimates concern years 1990, 2000 and 2003, with urban/rural differential being 19.3%, 23.7% and

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<sup>32</sup>Detailed description of the items and the dataset can be found at <http://laborsta.ilo.org/applv8/data/to2ae.html>

<sup>33</sup>Considering only cases where fuel was more than 2% or less than 20% of the total BBB.

<sup>34</sup>The FAO data were gathered during the 4th and 5th of May 2015 from the webservice available at <http://www.fao.org/gIEWS/pricetool/>, and the WFP data from <https://data.hdx.rwllabs.org/dataset/wfp-food-prices> on the 3rd of February 2016.

<sup>35</sup>Global Financial Data, Global History of Currencies dataset downloaded from here, accessed on 16, July 2014.



26.5% respectively. Finally, for Indonesia Asra (1999) estimates the differential at 13% for 1987 and at 16% at 1993 and 1996. For these three countries, and for the years between price differential data-points, the linearly interpolated value is used, and the last available value is applied for years outside of those periods. For any other country, a price differential would be of rather limited practical use, since not both rural and urban distributions are available.

### 3.3.3 Estimated Bare Bones Baskets

In total, 1982 BBBs have been priced directly from data in the period 1985-2014, with the aforementioned limitations, distributed as shown in figure 3.2. In the years 1985 until 2008, an average of about 70 developing countries have a priced BBB per year directly from original prices. Also on average the linear programming can identify the cheapest product combinations, that would yield the needed MDER caloric target and the specific protein amount, among about 12 relevant products with available prices.<sup>36</sup> There are, however, two important issues that dictate the use of imputation techniques for missing prices. First, the need to have both priced BBBs and distributions from PovcalNet for the same years for a given country. Second, the bias introduced when missing prices of the otherwise cheapest products occur only in some years. For example, take the case that in a country we have the price for maize for three consecutive years, and the price for rice for the first and the last of those years. Assuming further that rice is the cheapest nutritional source, the missing price for rice would artificially inflate the value of BBBs for that year. This happens, not because there was actually no rice in that country for that particular year, but because the dataset did not contain it.

To overcome these shortcomings food CPIs have been in principle applied to impute the missing prices. Occasionally food CPIs have been complemented by other more generic CPI types, such as average consumption CPIs. All CPI data are drawn from ILO, FAOSTAT, IMF, the World Bank and the Clio Infra dataset. After exhausting available CPI options, the average price change in the available prices of the dataset is used to estimate the price change for other products of the same category. If no other products were available from the same category the price change in staple foods is utilized instead. In the process, the error introduced by the imputation is ball-parked. For that purpose, a standard deviation of 20% is used for original prices from ILO, FAO, and WFP, on the basis of the deviation present in the original price data when more than three sampling locations are available per product, country and year combination. When the imputation is done for a year that follows one with available price data the assumed uncertainty increases by 1

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<sup>36</sup>This number of relevant products does not include fish or meat items. It represents mostly staple food items, complemented with bean/peas.

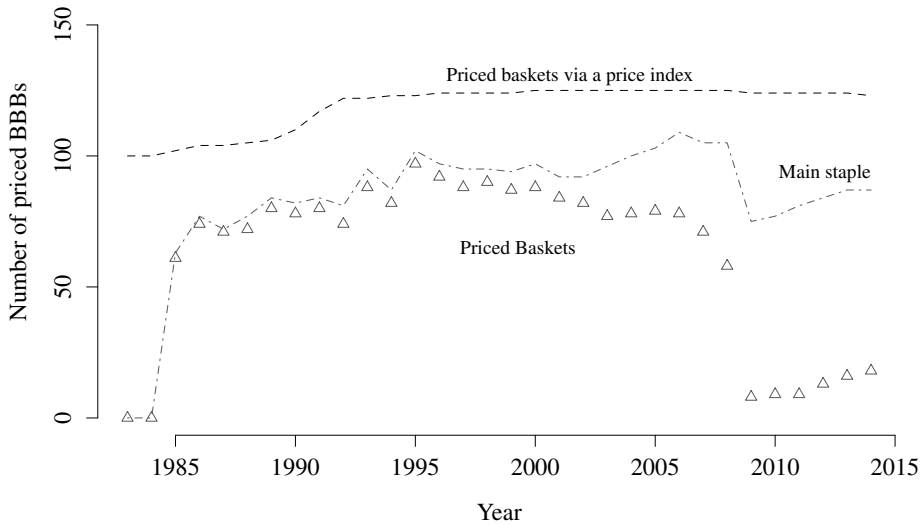


Figure 3.2: Priced BBB per Year, globally 1983-2014

percentage point by convention. For every additional year of distance between a missing price and the closest year with available price in the original data, an extra percentage point is added to the uncertainty level up to an overall maximum of 30%. This uncertainty is later propagated in the estimation of the poverty rates. In the case of a price imputation between given prices, there are two ways of estimating a value for that year. Either by starting from the later year going back using a CPI rate, or by starting from the earlier year and then going forward. Here the average of the two approaches is applied, weighted by the distance of the imputation year and the upper and lower years with available data. The data point of the year closest to the imputation year gets the higher weight proportionally.

Using this technique a total of 3679 BBBs have been priced for the period 1983-2014. Here the linear programming can choose from about 25 priced staple food or beans/peas products on average. The available estimates translate to about 120 per year, out of the 125 developing countries in the price datasets. This is shown on figure 3.2, alongside the BBBs priced only using the original data. To add some perspective the price availability of the staple food component in the original data is also shown. In the final poverty estimates the overall population coverage achieved throughout the developing world using these baskets is higher

than 85.2% on average. Lowest coverage is 76% in 1983 and highest is 1995 at 88.3%.

### 3.3.4 Household survey consumption and income distributions

With respect to the distributional data, PovcalNet contains data on consumption or income distribution for 165 countries or territories, since 1981.<sup>37</sup> The distributional data are available in terms of both 2005 and 2011 PPP international dollar for most countries.<sup>38</sup> To make the conversion back to nominal terms, the actual CPIs applied by the World Bank were used, along with the appropriate PPP exchange rates and the aforementioned data for currency denomination.<sup>39</sup> Since our target is to maintain the welfare level of those at the poverty line constant, it is important that in most relevant occasions the PovcalNet distributions concern consumption, since in those distributions own production is accounted for.<sup>40</sup>

As in the case of the regional and global aggregates presented in PovcalNet and Chen and Ravallion (2010, 2004), one needs to devise a way to align countries' consumption or income distributions to get the yearly estimates with acceptable coverage. For having a better comparability of the results, I follow their methodology. The basic idea of the method consists of using the evolution of a national accounts statistic, typically GDP per capita or household final consumption per capita, to increase or decrease the average of the distributions for the years without distributional data. The selection of GDP per capita or household final consumption is based on the per country data availability. When the year of interest lies anywhere between two available distributions, then both distributions are used and two different consumption or income averages are computed and two poverty rates are thus produced. Consequently, I take the weighted average of the two rates, with the one resulting from the distribution of the year closest to the year of interest tak-

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<sup>37</sup>In case both consumption and income distributions are available, the consumption one is preferred, following (Ravallion, 2013). Also note that due to the availability of prices the period investigated here begins in 1983.

<sup>38</sup>In principle the 2011 rates are applied, but for a few countries PovcalNet still uses the 2005 exchange rates. Those countries are Bangladesh, Cabo Verde, Cambodia, Laos and Jordan. Since there is no alternative I follow PovcalNet in this choice. The aggregated estimates here only refer to countries with 2011 PPP data at PovcalNet.

<sup>39</sup>For the few country/years that PovcalNet has no CPI, the available figure from the World Bank is used. For China in 2014 the official rural and urban CPI rates were taken from <http://www.stats.gov.cn/tjsj/ndsjs/2015/indexeh.htm>, and for the 2013 and 2014 rural and urban CPIs for India were taken from <https://data.gov.in/catalog/all-india-consumer-price-index-ruralurban>.

<sup>40</sup>Using a slightly updated version of a script provided by Dykstra et al. (2014a), and the BBBs as poverty lines, the poverty estimates for the BBB based poverty lines are obtained by querying PovcalNet directly. This treatment bypasses any discrepancies between the two datasets and allows direct comparisons of BBB absolute poverty estimates with those of the World Bank.

ing the higher proportional weight. If only one distribution for a previous or a later year exists, then only that single value is extrapolated using the national account statistic.

### **3.3.5 Uncertainty**

Data used in global poverty estimates are not without important limitations (Deaton, 2010a). Simply acknowledging this feature and carry on to provide plain point estimates is, however, far from satisfactory. Antithetically, an important role should be attributed to uncertainty in terms of interpretation of the results, at the very least because in many countries the poverty line is positioned at a point where the gradient of the distribution is a relatively steep one. This implies that a small error in the estimation of the actual level of the poverty line implies a larger one on the level of the poverty rate. In principle all data treatments and problems discussed above are sources of uncertainty and errors in the estimates. In the present treatment not all sources of uncertainty are accounted for. Those considered include price uncertainty by following a simple convention, uncertainty in energy required for heating and cooking, uncertainty in the number of persons per household, and uncertainty in the various budget shares applied. All the poverty estimates in the results that follow are reported with one standard deviation, as this obtains from error propagation.<sup>41</sup>

## **3.4. Bare Bone Baskets in perspective**

### **3.4.1 Bare Bone Baskets as a price index**

In order to empirically establish the discrepancy between the average consumption price index for the entire population, and the evolution of the prices that are most relevant to those living in absolute poverty, the relation between the two indexes is investigated. Figure 3.3 shows the evolution of the ratio of the CPI and BBB expressed as a price index with their 1990 values normalized to 100.

Overall, figure 3.3 supports the point that using a CPI which focuses on the average consumption habits tends to substantially skew the picture of the evolution of prices that are most relevant to those living in absolute poverty. The intensity of this differential varies considerably from country to country. China represents a distinctive case in this comparison. Until 1992 the implied underestimation of price changes is minimal. In the 1993-1995 period, the BBB price index moves with a

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<sup>41</sup>Testing for statistical significance in the difference among the various estimations of poverty rates requires considerably more information about the scattering of the poverty rate estimates than gathered here. Such an investigation stretches beyond the scope of the present paper.

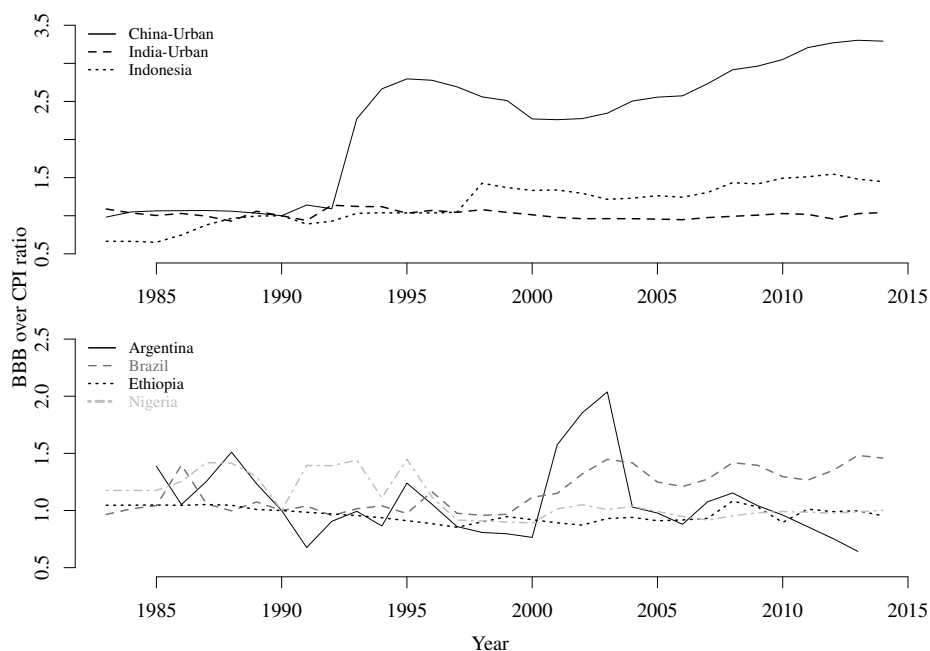


Figure 3.3: Evolution of the BBB over CPI ratio for selected countries, 1983-2014. For both the base year is 1990. Note the scale difference on the y axis between the two panels.

much larger pace than either the urban or the—not shown here—rural CPIs. This is followed by a relative slow down of the BBB price index from 1995 until 2000. Then BBB clearly accelerates again in the post-2000 period. India, in contrast, demonstrates a very modest difference in the evolution of the two indexes for the entire period. For Indonesia the BBB price index almost continuously accelerates from 1983 up to the sharp peak in 1998. This peak comes after the 1997/1998 food crisis episode, caused by a combination of drought, forest fires and massive capital outflows as reported by the World Bank<sup>42</sup>, and related food shortages (Soekirman, 2001). In the post-1998 period the ratio of the two indexes continues to vary, with some milder discrepancies.

On the lower panel, Argentina demonstrates the most extreme variation between CPI and the BBB index. The most sharp acceleration of the BBB occurs during the onset of the Argentinian financial crisis in 2001/2003. Similarly, in Brazil accelerating spikes are present for the most part. Only during 1987-1995 the discrepancies are substantially mitigated. Antithetically, in the case of Ethiopia the

<sup>42</sup>General Food Price Subsidies in Indonesia: The 1997/1998 Crisis Episode

two indexes evolve largely in agreement for most of the period, with CPI gaining speed against BBB for the greater part until 1997. Only during the 2007/2011 period the two indexes evolve in relatively larger disagreement. Finally, in Nigeria sharp discrepancies are identified in the first part of the period until 1997. For the remaining of the period, Nigeria shows milder differences among the two indexes, that only become apparent during the 2000/2002 period.

### **3.4.2 Bare Bone Baskets in dollar terms**

Figure 3.4 makes the direct comparison between the dollar-a-day and BBB based poverty lines. For this purpose the BBB poverty lines are expressed in 2011 PPP dollars. It is clear from the figure that the assumption that the “dollar-a-day” line provides an internationally constant standard in terms of welfare does not hold in practice, although it is methodologically required to. Note in addition that methodologically only for 2011 a direct comparison with the 1.90\$/day iPL makes sense. For that benchmark year the figure clearly points out that iPL is overestimating global absolute poverty compared to the consistent common achievement approach, for all but two developing countries (El Salvador and Venezuela). In that year the lowest BBB poverty line stands at \$0.27 for Namibia, the median at \$1.07 and the maximum at \$2.74 for El Salvador.

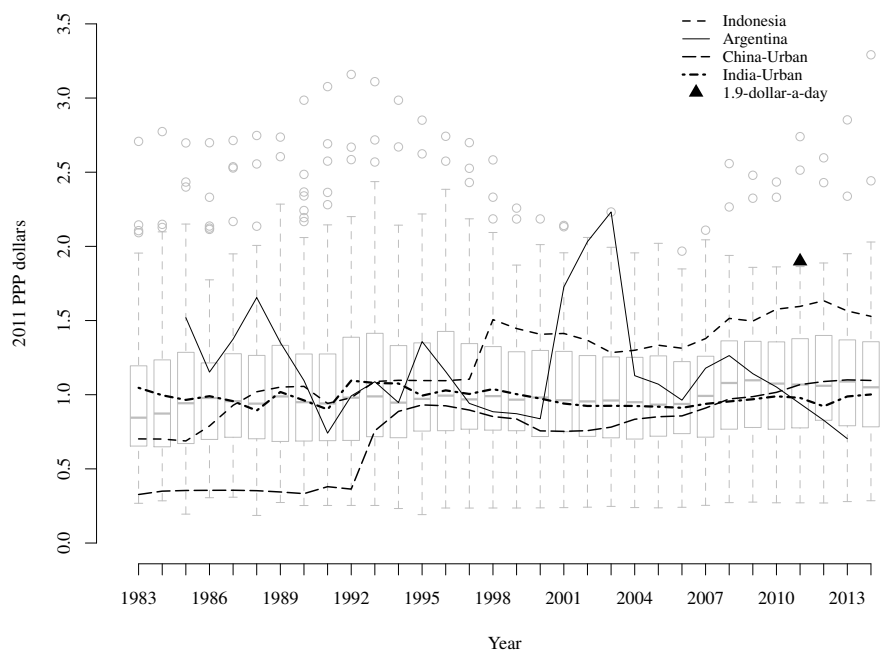


Figure 3.4: Evolution of BBB poverty lines expressed in 2011 PPP dollars, 1983-2014

Note that for any other than the benchmark year there is no equivalent iPL to compare to. That is the result of having one benchmark year for the ICP. It is not possible to estimate an iPL for, let's say, 2010 by simply correcting the 2011 iPL for the CPI in the reference country of the ICP (which is the USA) (Ravallion, 2010a). Nevertheless, for all the non-benchmark years the BBB values expressed in PPP dollars provide an understanding of the fluctuation of the BBB poverty lines, either in relation to the same country's BBB value in 2011, or in comparison to the other country's BBB poverty line for the same year. Thus even if there was a 2010 ICP round, it would be extremely unlikely that the BBB poverty lines would largely coincide with a 2010-based iPL.

The central point remains evident from the figure. The iPL applied by the World Bank does not consistently correspond to the same type of poverty, in terms of a reasonably defined welfare, in different years and locations. If that were the case then the variation among the BBB poverty lines for the benchmark year should have been quite modest, only representing some uncertainty in pinpointing the exact iPL level in dollar terms. This cannot be concluded from the figure. The common achievement method, delivers estimates of the same type of absolute poverty that range, in 2011 PPP dollar terms, from a remarkably low \$0.19 for Uganda in 1988,

up to \$3.29 for Venezuela in 2014, and a median value of \$0.99 for the entire 1983-2014 period.

In the same figure a number of important countries are traced by lines that mark the evolution of their BBB values. In the evolution of the BBB values expressed in PPP dollars, there are some pronounced episodes that introduce volatility. The 2001-2003 pronounced spike in Argentina for example, relates to the crisis that struck the country in the same period. The hump shown on the graph regarding Indonesia during 1998 relates to the 1997/1998 food crisis episode mentioned above. India is the only country shown here that has a rather smooth upward trending evolution without such large episodes.

For China, a big hump in the BBB values takes place within a few years, from 1993 to 1995. It is important to note that this is not a result of imputation, but it is driven by available original price data.

Figure 3.5 shows the BCS poverty lines expressed in 2011 PPP dollars. BCS results confirm the main conclusion that the basic BBB poverty lines have supported. Volatility of the BCS values in 2011 PPP dollar terms maintains throughout. At the benchmark year the minimum value is found in Uzbekistan at \$1.26, the maximum value is found in Angola at \$12.30, and the median stands at \$3.09. For the entire period the minimum value is found in Tajikistan in 1995 at \$0.96, the maximum in Angola in 1991 at \$20.12 and the median stands at \$3.71. The variations in the evolutions of the four traced countries are less pronounced due to the scale; still present nonetheless. The overall similarities with figure 3.4 imply that the identified inconsistency of the iPL and the “dollar-a-day” method is not explained by the explicit methodological choices or the low welfare level targeted in the BBBs, as it survives the different computational treatments applied to obtain the BCS.



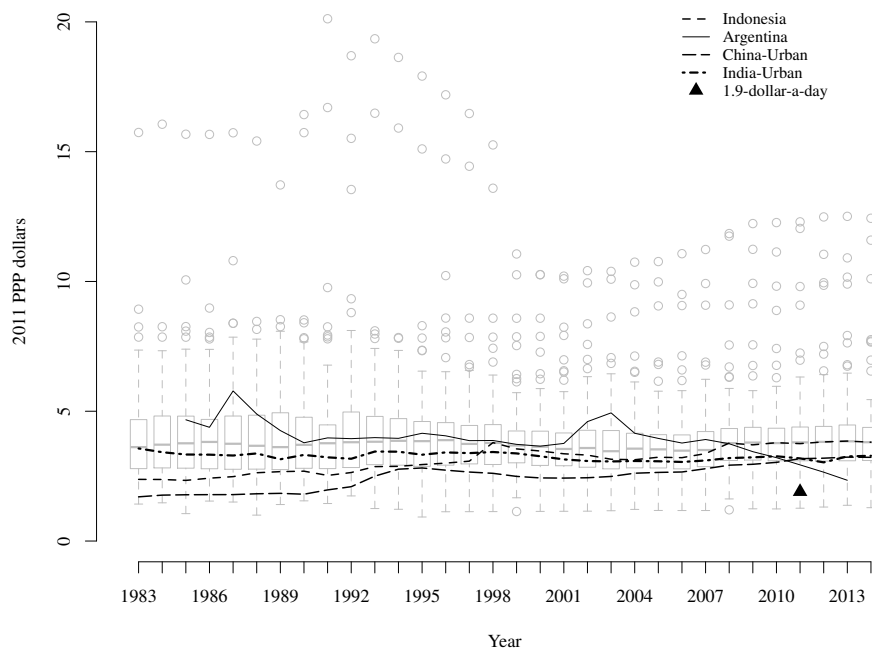


Figure 3.5: Evolution of BCS poverty lines expressed in 2011 PPP dollars, 1983-2014

## 3.5. Global absolute poverty estimates

### 3.5.1 Developing World

The absolute poverty rates of the Developing World are shown in figure 3.6. The figure shows both types of BBB based poverty lines, along with the available estimates of the World Bank. As anticipated the picture shaped by each type of poverty lines differs substantially. For the BBB poverty lines, a weak upward trend characterizes its aggregate point estimate evolution from 1983–were the poverty rate is estimated at 5.5% (3.8, 7.5)<sup>43</sup>–until 1994, with poverty rates at 8.9% (6.1, 12.4).

<sup>43</sup>This notation should not be read as a confidence interval.  $\pm 1$  SD of the BBB value gives in this case 3.8% and 7.5% respectively, or in the simpler notation (3.8, 7.5) as reported here.

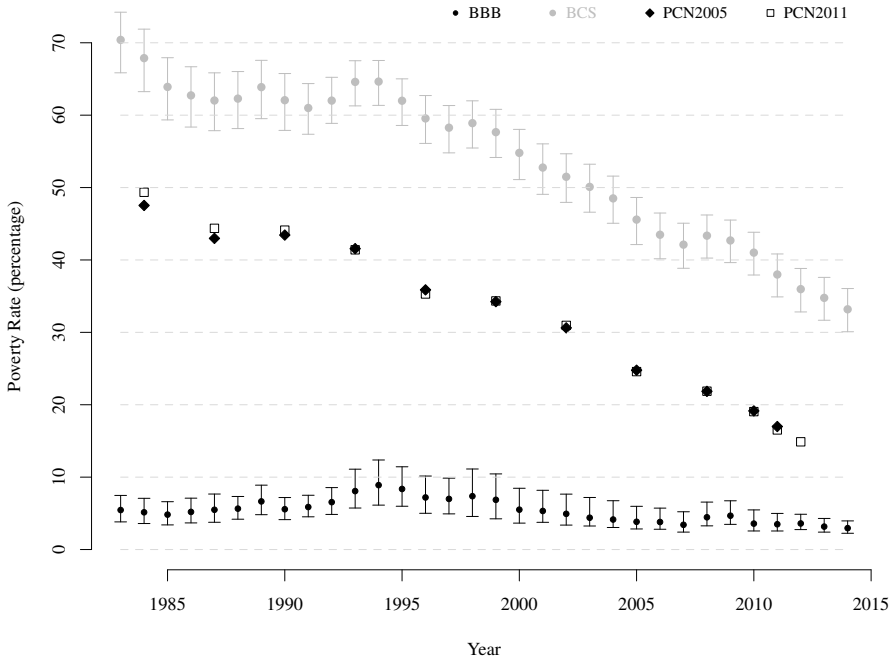


Figure 3.6: Evolution of poverty in the Developing World, 1983-2014

In 1990, which is the reference year for the Millennium Development Goals, BBB poverty stands at 5.5% (4.1, 7.2). A gradual decrease starting in 1995 lasts until 2007, where it reads 3.4% (2.4, 5.2). The first two years after the onset of the 2007/2008 Global Food Crisis shortly interrupt this mild trend, and in the post 2009 period the BBB poverty rate remains practically constant. In 2014 BBB poverty stands at 3% (2.2, 4). These results show that, in terms of levels, on the one hand the target of alleviating absolute poverty is not as far off as was thought of, but on the other hand, absolute BBB poverty has shown remarkable persistence throughout the period. The difference with the PovcalNet estimates is enormous throughout. Comparing the 1990 and 2014 estimates leaves little room for celebrations over the achievement of halving absolute global poverty between 1990 and 2015<sup>44</sup>. The same insight is supported using the BCS poverty lines as well, thus it does not result from the very low welfare level of the BBB poverty lines.

With respect to the BCS poverty lines the estimates are located at a much higher level, and in all cases higher than the PovcalNet estimates on average. In 1983, BCS poverty level begins at 70.4% (65.9, 74.2), and its average follows a shallow

<sup>44</sup>Millennium Development Goal 1: “Target 1.A: Halve, between 1990 and 2015, the proportion of people whose income is less than \$1.25 a day”, taken from <http://www.un.org/millenniumgoals/poverty.shtml> on June 6, 2016.

u-shaped trajectory until it reaches a local maximum in 1994 at 64.6% (61.4, 67.6). From that point onward it follows a downward trend until 2014, with only an interruption following the aforementioned Great Food Crisis. At the end of the period the BCS poverty stands at 33.2% (30.1, 36.1).

The vast differences among BBB welfare level and the iPL can be attributed on two elements. First, the much lower costs of bare bones subsistence compared to the \$1.9 value for the vast majority of the countries and years. And second, on the differential between CPI and the BBB price index. The also very large differences of iPL with BCS, especially on the later years of the period, is attributable to the inability of the iPL to encapsulate expenses that are necessary in escaping absolute poverty as described in international treaties and conventions.

Figure 3.6 might give the impression that the BBB methodology does poorly in specifying welfare levels with some accuracy. The variance of the one standard deviation implies that there is considerable room for uncertainty. However, it needs to be noted here that the “dollar-a-day” methodology is far less successful in that respect. The standard deviation for the “\$1.90” iPL is \$0.68, and the null hypothesis for normality of the underlying NPLs cannot be rejected<sup>45</sup>. Therefore the equivalent—to the treatment of the BBB poverty rates—reading of the “dollar-a-day” global poverty for 1990 is 44.12% (19.49, 58.48) and for 2012 is 14.88% (4.63, 26.63). The variance in those estimates is by far greater than the one achieved by the BBB methodology. Using the 95% confidence interval for the iPL on the level of national poverty lines, then the reading of the “dollar-a-day” global poverty for 1990 is 43.56% (instead of 44.12%) with a corresponding 95% confidence interval of (32.37, 51.91) and for 2012 it is 14.54% (instead of 14.88%)<sup>46</sup> with a corresponding 95% confidence interval of (8.88, 20.6). Thus the relative uncertainty of the iPL global absolute poverty estimates is on average above 20% for 1990, and around 40% for 2012; both quite far from satisfactory.

In terms of the number of people living in absolute poverty, shown in figure 3.7, each set of poverty lines shapes a different picture, while the underlying scattering translates up to several hundreds of million of people.<sup>47</sup> With respect to the most extreme form of poverty, captured by the BBB absolute poverty lines, the picture is quite unpleasant on the aggregate trend. In 1983, the population living in BBB level absolute poverty was 207.73 million (145.44, 284.59), and by 1994 this

<sup>45</sup>The quotes around the 1.90 denote that the actual mean value is not \$1.9, but rather \$1.88. Several normality tests were applied (Shapiro-Wilk, Pearson chi-square, and Anderson-Darling among others) all which did not reject the null hypothesis for normality.

<sup>46</sup>The differences on the mean value are caused by the use of the actual average of the underlying NPLs, which is 1.88, instead of the adopted average of 1.9.

<sup>47</sup>For reasons of comparison with PovcalNet, we apply the same rule for getting the number of people living in poverty. That is the poverty rate of the region is applied to the entire population of the region regardless of coverage.

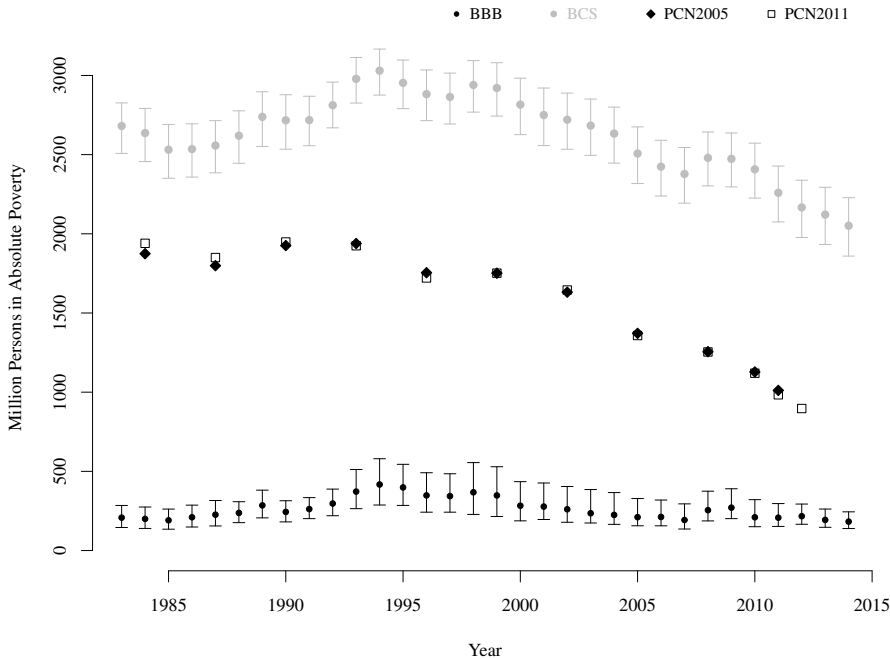


Figure 3.7: Evolution in the number of people living in absolute poverty Developing World, 1983-2014

had increased to 416.98 million (287.48, 579.8), which is about double the 1983 average estimate. By 2014 the estimate drops at 182.55 million (138.79, 244.34), which is the only year for which its point estimate is lower than 1985's 191.04 million (134.76, 261.66).

The number of people living in conditions of the more demanding BCS absolute poverty lines are much higher than those of PovcalNet. More often than not this difference exceeds one billion people. In 1983, the BCS estimate stands at 2680.91 million (2507.8, 2826.6), and in 1984 at 2636.23 million (2456.44, 2791.85). For 1984, which is the first year with both BBB based and PovcalNet estimates, the difference in point estimates with PovcalNet is at about 700 million people. By 1994, the BCS point estimate has reached its maximum at 3030.02 million (2875.85, 3166.61). By 2012, which is the last year that PovcalNet has an estimate for, this difference has increased at roughly 1.3 billion people. In 2014, the number of people living in BCS absolute poverty stands at its lower point at 2051.21 million (1859.4, 2228.44). At this welfare level BCS poverty was lower as point estimate than the 1985 local minimum, only after 2005.

Figure 3.8 demonstrates the geographical distribution of the people living in

BBB absolute poverty in terms of the point estimates. As it is evident from the graph, Sub-Saharan Africa is constantly the largest contributor on global scale for this type of poverty. The second largest contributing region depends on the specific year. In the 80s it is South Asia that occupies the second place, while during the 90s it is the East Asia and Pacific region. In the 00s Latin America and Caribbean has the second place. The rankings shown in figure 3.8 constitute an almost complete reshuffling compared to the PovcalNet rankings (see more details about the PovcalNet rankings below).

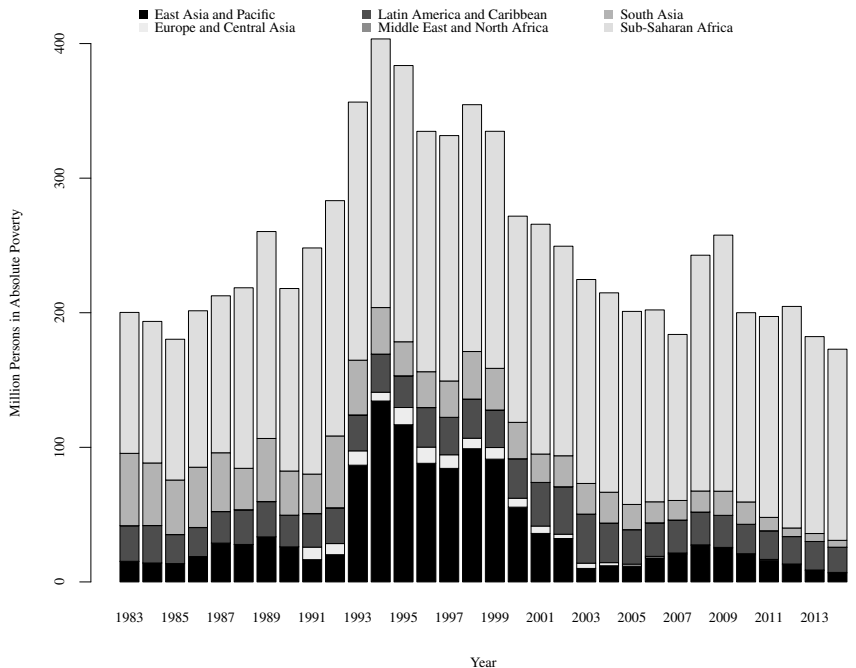


Figure 3.8: The geography of BBB based global absolute poverty on regional level, 1983-2014. Note that the region Middle East & North Africa is not visible due to the very low number of people living in absolute poverty in that region.

Figure 3.9 paints a largely different picture that do the lower absolute poverty BBB lines. As in the case of PovcalNet rankings, it is East Asia and Pacific that tops the rankings for the most part of the period, with South Asia in second place. In PovcalNet, East Asia and Pacific drops to second place in 1999 from South Asia, while in BCS rankings this happens in 2005. South Asia then is surpassed by Sub-Saharan Africa in 2011 in PovcalNet, but according to the BCS estimates it remains the highest BCS poverty contributor until the end of the period. In BCS terms, the region of Latin America and Caribbean ranks consistently in fourth place.

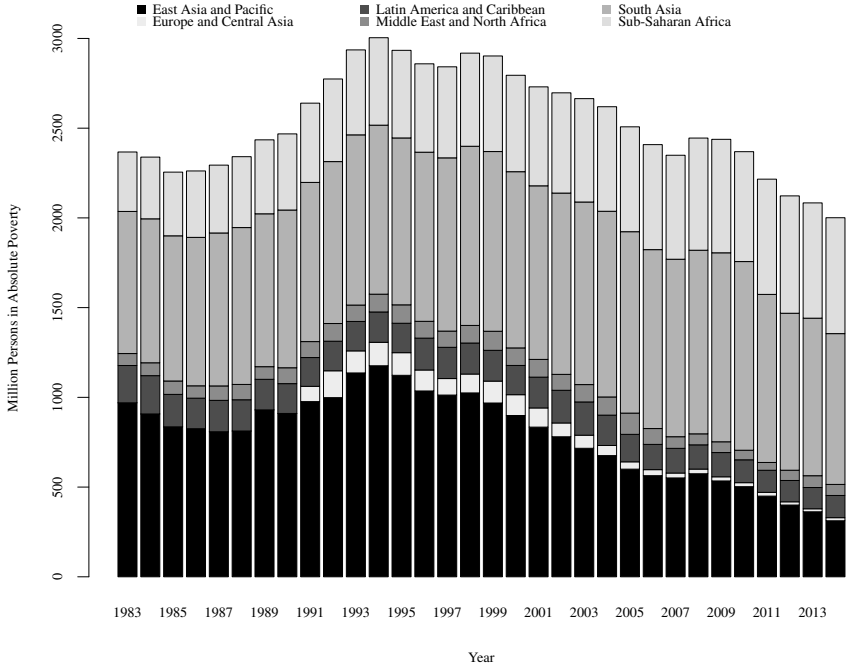


Figure 3.9: The geography of global absolute poverty on regional level, 1983-2014.

### 3.5.2 Regional level

Figure 3.10 shows that while in South Asia the BBB poverty rates are typically below the 5% in point estimate, the BCS type of poverty have rates that are more than ten times higher. In 1983, BBB poverty rate is 5.6% (3.2, 8.9) and BCS poverty is 82% (79.2, 84.3). By 1995, these rates have dropped to 2% (0.8, 4.9) and 73.9% (70.3, 77) respectively. This slow, but persistent trend continues until 2010 when the rates have dropped at 1% (0.3, 3.8) and 64.5% (60.4, 68.1) respectively. Beyond that, and until the end of the period in 2014, both poverty rates are at their lowest point with BCS demonstrating accelerated reduction. By 2014 the poverty rates are at 0.3% (0.1, 1.2) and 48.8% (44.3, 53.1) respectively.

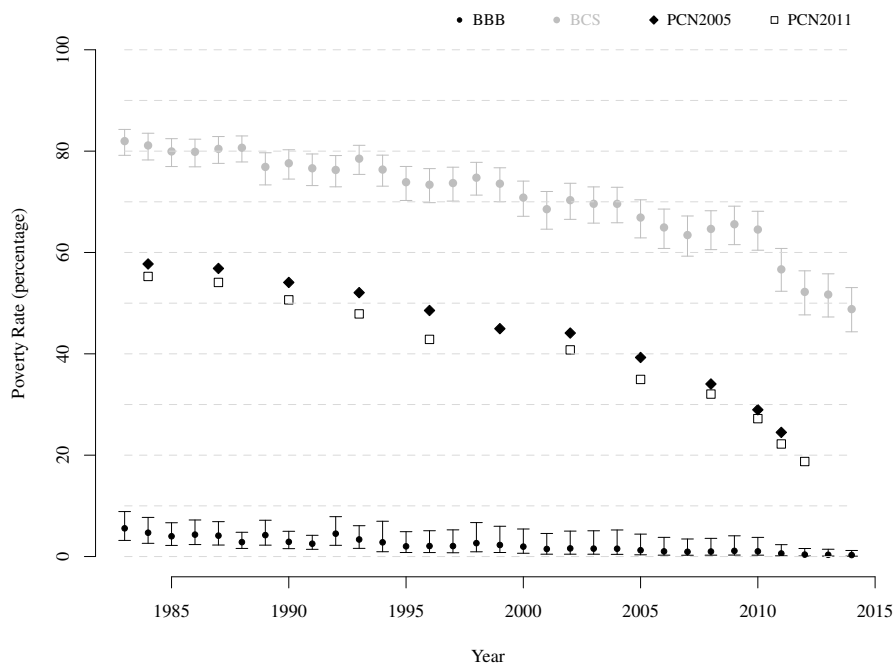


Figure 3.10: Evolution of absolute poverty rates in South Asia, 1983-2014

For the region of East Asia and Pacific BBB poverty, as shown in figure 3.11, demonstrates a more volatile picture than in South Asia. Despite the single digit BBB poverty levels throughout the period, a disturbance occurs in the greater part of the 90s. It tops in 1994 at 7.9% (4, 12.2). BCS lines also capture this disturbance. The right tip of the u-shaped trajectory followed by BCS lines in 1983-1994 period stands at 69.4% (66.1, 72.4), marginally higher than the 67.9% (62.1, 72.9) estimate for 1983. All of those peaks follow the sudden increase of the poverty lines in this period identified in the case of China. After 1994 and for the next 20 years, this region demonstrates strong decreasing trends for BCS lines. Within this period the BBB poverty has recovered from the 1993/1994 disturbance. Beyond 2002 it remains close to zero levels. By 2014, BCS poverty stands at 15.5% (13.9, 17.1). On a point estimate level this figure represent a more than four-fold decrease compared to 1983 or 1994.

The patterns of single digits, or close to zero, BBB rates observed in the previous two regions are far from identifiable in the case of Sub-Saharan Africa shown in figure 3.12. For 1983, BBB absolute poverty stands at 25.1% (20, 30) a clear indication of the unprecedented poverty hardships faced by people in Sub-Saharan Africa, compared to any other region (see below). By 1995 the BBB poverty rate reaches its maximum at 35.2% (30.5, 39.8). The gradual drop in BBB poverty is

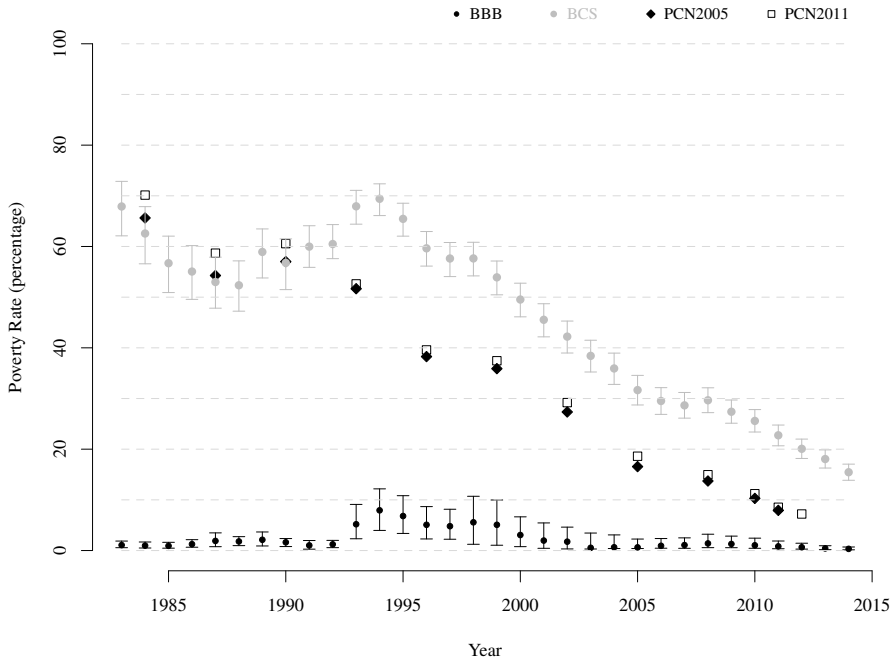


Figure 3.11: Evolution of absolute poverty rates in East Asia & Pacific, 1983-2014

interrupted in 2008/9. A local maximum in those two years tips at 22.4% (18.3, 26.4). The relative intensity of this local maximum, compared to the similar maxima in other regions, is indicative of the relative intensity that the Great Food Crisis in 2007/8 hit the BBB absolute poor in the region. By 2014 the rate stands at 14.6% (11.4, 17.9) which is about as much as the BCS point estimate for East Asia and Pacific.

BCS poverty in the region stands at 79.4% (76.5, 81.6) for 1983 and moves generally upward until the peak of 1995 at the sky high 85.8% (83.5, 87.4). Its course then turns downward until its lowest estimate of 66.3% (61.8, 69.8) in 2014, while the 2008/9 interruption remains observable.

Figure 3.13 shows the poverty rates for Latin America and Caribbean. BBB absolute poverty rates are found on average above those in the two Asian regions presented. This is in sharp contrast with the PovcalNet perspective. In 1983, the BBB poverty rate is at 6.9% (5.3, 8.5). Thereafter the point estimates are dropping in 1985 in a 5-6% region from which they escape only after 2004. The clearly observable local maximum in 2008/9 found in the previous regions appears to be masked. By 2014 the BBB rate drops at its lowest point at 3% (2.5, 3.5). In terms of BCS poverty the region of Latin America and Caribbean is typically found lower



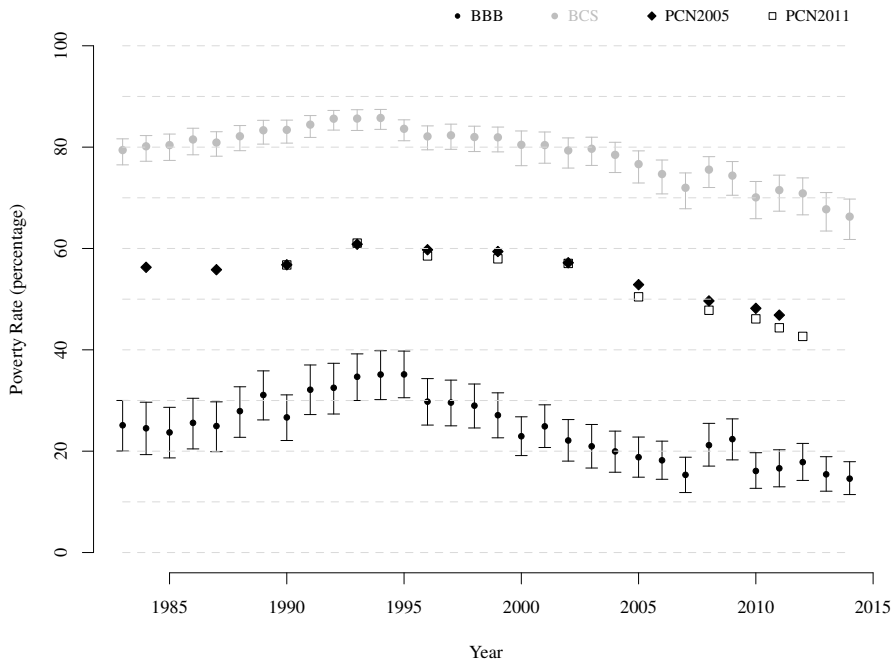


Figure 3.12: Evolution of absolute poverty rates in Sub-Saharan Africa, 1983-2014

than the two Asian regions above. When considered together with the observation that BBB poverty in this region is on average higher than its Asian counterparts, this implies that Latin America and Caribbean concentrates more extreme forms of absolute poverty relative to Asia, while, contrary to Sub-Saharan Africa, it manages to maintain poverty rates at higher welfare levels relatively low. By 2014, the BCS poverty rate settles at 19.9% (16.4, 23.3), and it is the only region showing a tendency to increase at the end of the observation period. Still that rate is less than half of the 1983 point estimate.

Figure 3.14 shows the poverty rate estimates for Europe and Central Asia, but only for the 1991-2014 period due to low regional population coverage in the previous years. For the best part of the 90s this region is largely comparable in BBB terms to South Asia and East Asia and Pacific. The BBB poverty rate peaks in 1995 at 2.7% (1.7, 3.8), and fades to marginal levels by the late 00s. In 1992, BCS poverty rate stands at 32.1% (30, 34.2), which represents a surging point estimate increase from the 18.3% (16.3, 20.2) at the year before. It then follows an m-shaped trajectory until it gradually drops to 3.6% (2.9, 4.4) by 2014. This estimates is the lowest of its type among all regions.

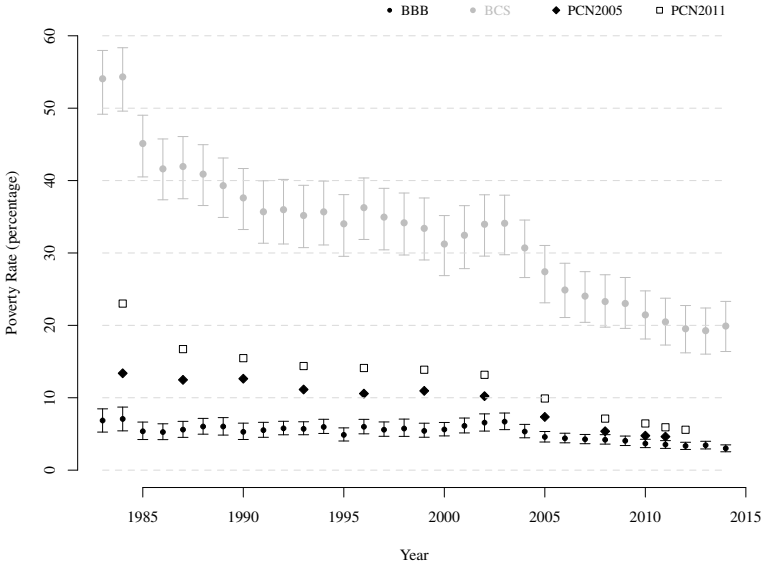


Figure 3.13: Evolution of absolute poverty rates in Latin America & Caribbean, 1983-2014

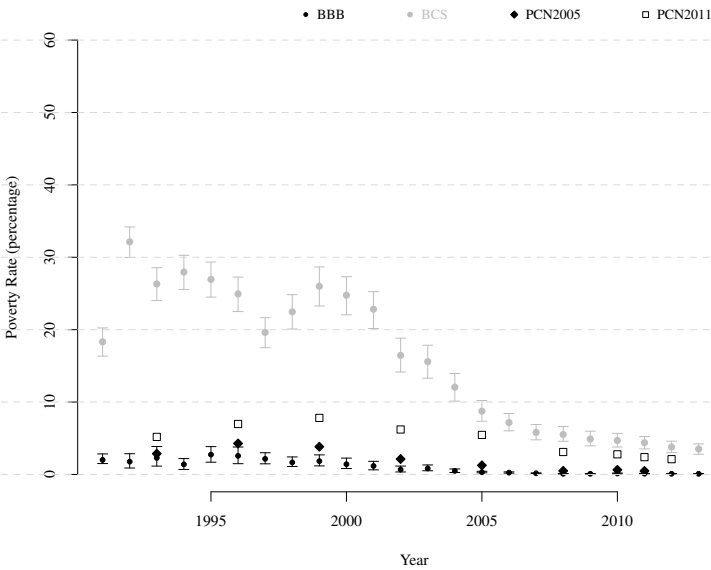


Figure 3.14: Evolution of absolute poverty rates in Europe & Central Asia, 1991-2014

In figure 3.15 the region of Middle East and North Africa is shown. Here BBB poverty is practically zero for the entire period. However, BCS type of poverty is quite present in the region. In 1983 it is estimated at 36.1% (29.6, 42.3). The maximum point estimate is found in 1995 at 40.2% (33.6, 46.4). After a peak at 38.7% (31.6, 45.3) in 2005, the BCS curve follows a strong downward trend until it reaches its minimum at 12.7% (9, 16.7) in 2011. Along with the region of Latin America and Caribbean, this is the only other region that shows an increase in BCS poverty during the last years of observation. By 2014 BCS poverty in the region reads 17% (12.2, 21.8). Finally, despite the similarities with Europe and Central Asia in terms of the 2011-based iPL, this region is considerably worse off in terms of the more demanding BCS welfare level.

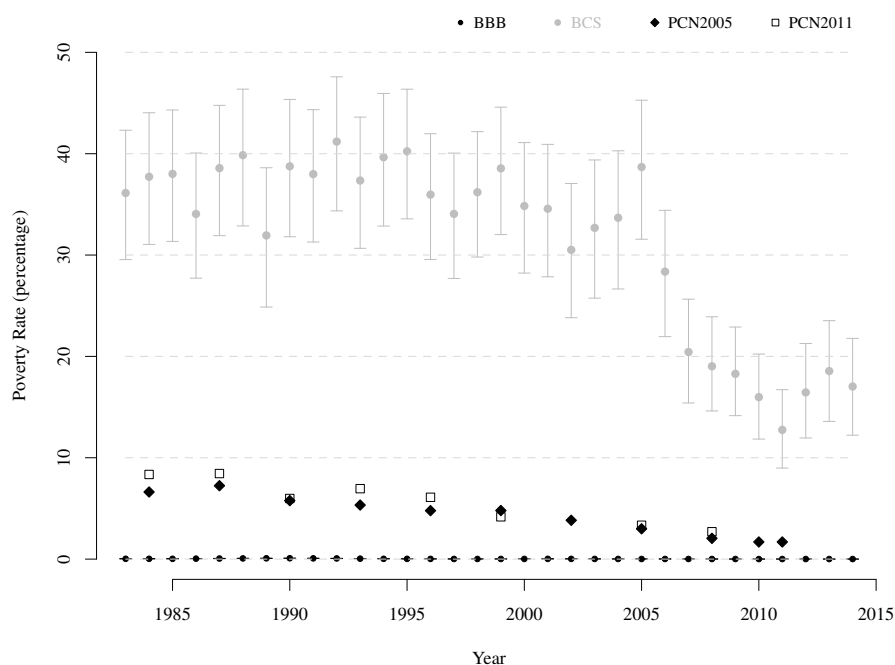


Figure 3.15: Evolution of absolute poverty rates in Middle East & North Africa, 1983-2014

### 3.5.3 Country level

Turning now on the country level the focus is first set on the two largest countries that also happen to have distributional data for both urban and rural areas. Figure

3.16 shows the estimates for urban and rural China.<sup>48</sup> From the perspective of BBB poverty lines, the two parts of the country demonstrate a characteristic difference. While urban BBB poverty remains at practically zero levels, the familiar hump already seen in figure 3.11 appears to be almost entirely attributable to the rural part of the country. The familiar peak of 1994 stands at 11.9% (6, 18) or 99.61 million (49.79, 149.76) people.

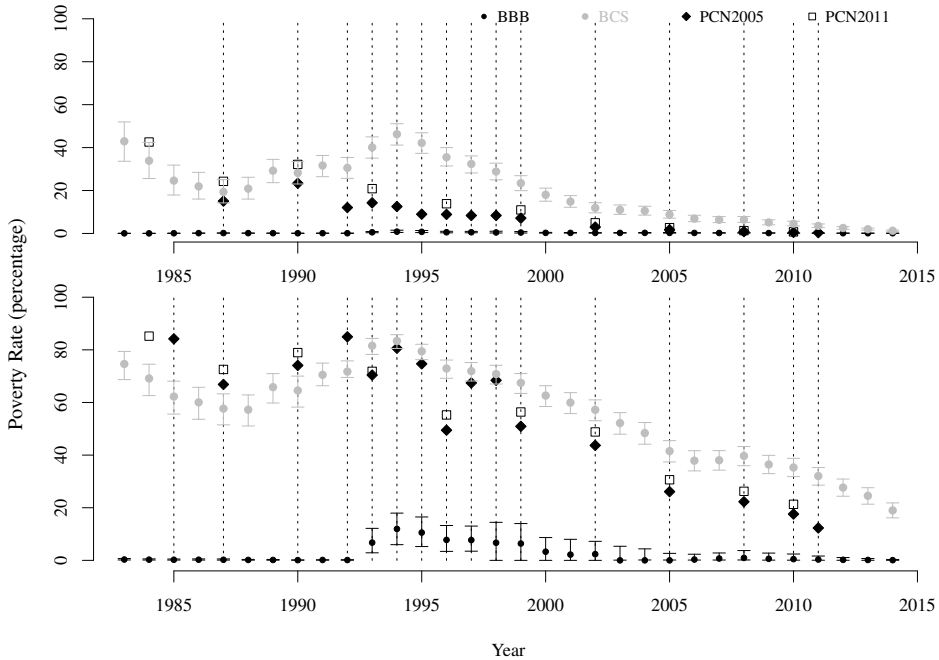


Figure 3.16: Evolution of absolute poverty in urban and rural China, top panel and bottom panel respectively, 1983-2014

In terms of BCS welfare levels the rural region in China is again the one with the highest poverty prevalence. At the peak of 1994 the estimate is as high as 83.4% (80.5, 85.8) or 695.3 million (671.45, 715.29) people. Nevertheless, in urban China BCS poverty reaches considerably high levels with a peak in 1994 at 46.2% (41.2, 51.1) or 165.49 million (147.31, 182.89) people.

While rural BBB absolute poverty rates in China are much worse than in the urban part of the country, the situation in India, shown here in figure 3.17, is relatively much more balanced overall. Indeed, the urban population here appears to be worse off but only marginally so. By the end of the period the differences in point

<sup>48</sup>Each figure in this subsection also marks with a vertical black dotted line the years with available distributional data from PovcalNet.

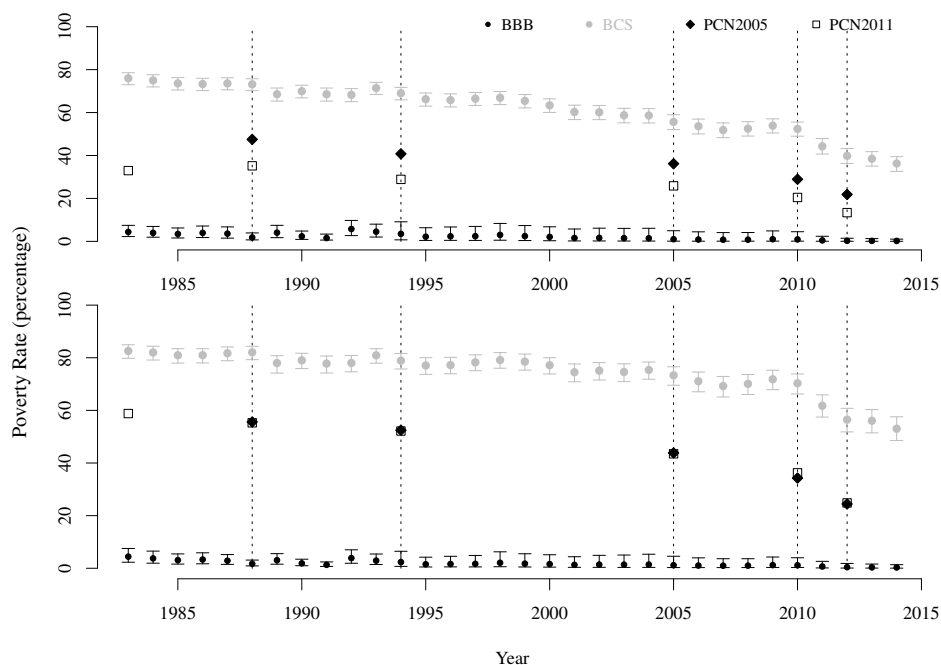


Figure 3.17: Evolution of poverty in urban and rural India, top panel and bottom panel respectively, 1983-2014

estimates among the two regions become larger. In BCS terms rural India stands at 53% (48.6, 57.6) or 464.57 million (425.5, 504.35), and in the urban regions at 36.3% (32.6, 39.5) or 152.1 million (136.67, 165.47). In comparison to urban China, population in urban India is worse off at both welfare levels. Comparing the rural areas among the two countries India is found worse off as well, but with the important exception of the years around the 1994 peak in rural China.

### 3.6. Conclusions

Utilizing a more than 100 years old methodology, two absolute poverty lines of different welfare levels have been specified and measured. The underlying inconsistency of the dollar-a-day methodology in measuring a specific standard of welfare level for each country has been substantiated at both welfare levels. Arguably the normative choices included in the methodology to track global absolute poverty should progressively incorporate the widest set of welfare elements found in the definitions of absolute poverty by independent international bodies and widely accepted international treaties. At the same time the most complete available data

are used to directly or indirectly estimate their costs. BCS poverty lines follow this principle to a large extent. However, an improvement of poverty at this higher levels does not allow for celebrations when those who needed the most are not seeing much improvement in their numbers, as shown by the BBB poverty lines. The world had to wait for nearly 30 years to see the number of people living under the bare bone minimum conditions drop as a point estimate. This is very far from satisfactory, or a reason to celebrate.

Differentiating the poverty lines among various welfare levels, brings up the differences in the types of poverty that are mostly relevant in the various countries and regions. Regions that for some years appeared of having the same level of poverty under an iPL, such as Sub-Saharan Africa and the two Asian regions, have been found to be facing poverty issues of very different type and intensity.

In terms of levels, the identified differences are explained by the deviations among the BBB-based poverty lines and the iPL for the reference year of the PPP rates. Away from the reference year the additional discrepancies are controlled by the differentials between the local CPI and BBB price indexes. Overall, the low welfare level poverty line shows less encouraging trends to those demonstrated by the iPL, while the high welfare line shows a more worrisome picture in the levels of global poverty than the iPL does. The iPL tends to compromise the two, by showing promising trends at relatively non-alarming levels. Regardless, this research indicates strongly that the World Bank should focus on specific well defended welfare levels such as to provide the proper framework in evaluating the success of its policies on a global scale. The lower the welfare level of poverty lines, the higher the importance of the level of the policy success since serious human rights violations may well be committed against those in the worst welfare positions (Pogge, 2011). In terms of point estimates it appears that MDG 1 will probably be just barely fulfilled by 2015, despite the World Bank's conclusion that this was fulfilled already in 2010. Nevertheless, this prediction ignores the considerable uncertainties in the estimates. Uncertainty about halving the poverty rate in the developing world between 1990 and 2015 remains at both welfare levels that are measured.

The variance in the estimates presented here is considerable. However, it is smaller than the equivalent variance under the "dollar-a-day" approach. Further, it has been shown that the systematic uncertainty in the "dollar-a-day" estimates is—unacceptably—large.<sup>49</sup> It is a puzzle why this very important issue in the measurement of things has not been questioned—to the best of my knowledge—in the literature so far.<sup>50</sup> Those of us who live in conditions of extreme deprivation most certainly worth a better methodological conduct. An exact testing of the statistical

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<sup>49</sup>A more appropriate investigation of systematic errors in the BBB estimates that would incorporate Monte Carlo simulations extends beyond the scope of this paper.

<sup>50</sup>More recently, recommendation 5 in Atkinson (2016) picks-up this point.

significance in the poverty rate estimates, that would consider not only the variance arising from the distributional uncertainties, but also from the systematic uncertainties in the definition and measurement of the poverty line is crucial for future work. Naturally, not doing so implies that we know more than we actually do about poverty and its evolution.

In the above, one should also consider that in the BBB-based lines, only the caloric content and a fixed amount of proteins are the target requirements for the food components. However, as pointed out by Kakwani (2003) “[i]deally, the construction of food poverty lines must take account of all six nutrients.”<sup>51</sup> This has been recently implemented for a group of countries by Allen (2016), and it presents itself as a natural extension of the poverty lines presented here. Such a step is likely to increase all the BBB based poverty lines. In addition, accounting for errors contained in the distributions; errors introduced by shifting distributions to years were they are unavailable; errors due to the quality of the price sources; and errors due to the estimation process of the PAL and MDER values is required as well.

Another important limitation that is shared among the BBB methodology and the “dollar-a-day” is the inability of both to account for any misallocation within households. This is of particular concern, and as shown by Klasen and Wink (2003) there are indications of strong misallocation, especially towards women. However, available data do not have the necessary level of detail that would allow us to address this particularly worrisome situation.

The presented uncertainties make a good case for better basic commodity price monitoring on nothing less than a global scale. While improvements have been made in this respect via the WFP and the FAO, and even if the frequency is much higher than the ILO’s October Inquiry, still the number of items collected is a small fraction of the ILO’s source. The same issue appears with respect to the number of countries covered as they only correspond to about 40% of what ILO’s October Inquiry covered. The traditional openness of ILO to make available the price data it gathers is an important component in measuring global poverty research. Keeping this—now interrupted—policy in place is highly recommended.<sup>52</sup> In addition, it is widely accepted that prices in rural areas are lower than urban ones. However, for the least affluent there is one additional element to consider. As noted by Ward (2009); Reddy and Pogge (2010), low income groups tend to face higher prices for the same goods.<sup>53</sup> This negative effect for the poor is captured neither in our data,

<sup>51</sup>The six nutrients are: calories, proteins, carbohydrates, fats, vitamins, and minerals

<sup>52</sup>Coincidentally I participated in a summer school on “Globalization and Inequality” organized by the University of Groningen in July 2016, where a presenter mentioned that as a member of a committee advising the ILO, he asked their representatives whether they know if anyone is using their price and wages data series. Apparently their response was negative, which may have contributed in the discontinuation of this long standing valuable statistical effort.

<sup>53</sup>On the matter, Rao (2000) finds relevant evidence for rural South India, and Biru (1999) for

nor in the data of the World Bank. At the same time the need for frequent, consistent and comparable consumption and income distribution data is one of equal importance.



## Chapter 4

# The confidence level of the First Millennium Development Goal: A timely first look

by Michail Moatsos & Achilleas Lazopoulos<sup>1,2</sup>

*“Extraordinary claims  
require extraordinary evidence.”  
Carl Sagan*

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The dollar-a-day method, applied in monitoring the UN's development goals against poverty, provides no confidence interval for the official figures of global poverty reduction, a practice that does not allow statistical testing. Using Monte Carlo simulations we construct confidence intervals that reflect, to a large extent, the data and methodological uncertainties involved, particularly the error introduced by the process of determining the International Poverty Line. These estimates identify a reduction of less than 5% between 1990 and 2015 at 95% confidence level, in stark contrast with the remarkable 73% reduction of global poverty reported in the World Bank official statistics published on September 18, 2018. At the same time, MDG1 obtains with a 77% confidence level. The cost-of-basic-needs method paints a more promising picture identifying a 34.4% reduction at 95% confidence level, while the confidence level at which poverty in 2015 was half of 1990 stands at 46%.

#### 4.1. Introduction

“[T]he margin of uncertainty for the global poverty estimates is so large that there must be serious questions about whether they are worth doing in anything like their current form”, Advisory Board member, *World Bank Commission on Global Poverty* (Atkinson, 2016, p.54)

“World Bank economists have often felt uneasy about the misleading precision with which our poverty estimates appear to become imbued in public debate, despite our best efforts to document in detail the very significant uncertainty involved in each of the various steps leading up to the final numbers.”, P. Romer, A.Revenga, & F.Ferreira, *A Cover Note to the Report of the Commission on Global Poverty*(The World Bank, 2016, p.5)

Both the Millennium Development Goal 1 (MDG1)<sup>3</sup>, aiming at the reduction of global extreme poverty rate by half between 1990 and 2015, and the Sustainable Development Goal 1.1 (SDG1.1)<sup>4</sup> which aims at its eradication, rely on our ability to compare global poverty rate estimates. However, both goals are thus far evaluated on the basis of World Bank's point estimates which do not allow for any

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<sup>3</sup>MDG1: “Target 1.A: Halve, between 1990 and 2015, the proportion of people whose income is less than \$1.25 a day” from <http://www.un.org/millenniumgoals/poverty.shtml>, accessed on March 14, 2017. The United Nations inform us on the same page that “The target of reducing extreme poverty rates by half was met five years ahead of the 2015 deadline.”

<sup>4</sup>SDG Target 1.1: “By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than \$1.25 a day” from <https://sustainabledevelopment.un.org/sdg1>, accessed on March 14, 2017.

meaningful statistical test to be applied in order to support or reject their success at a desired confidence level.<sup>5</sup> Before setting a framework for tracking the evolution and the success of SDG1.1, one should take careful stock with respect to the results concerning MDG1, while considering—in particular—the magnitude of the uncertainties involved. According to the World Bank’s official data MDG1 has been achieved 5 years in advance of its 2015 deadline,<sup>6</sup> with the official estimate for 2015 being issued in September 2018.<sup>7</sup> However, without the margins of error of the reported point estimates, one cannot know the confidence level at which this important claim remains obtained, and even ex post decide if the obtained confidence level is acceptable or not. Naturally, the same will apply to SDG1.1, a decade or so down the road.

To that end, in October 2016 the *Commission on Global Poverty*, presided by the late Sir Tony Atkinson, published a set of recommendations to the World Bank (hereafter also referred to as the Bank) on the issue of measuring global poverty (Atkinson, 2016). Recommendation 5 stipulates that, the Bank should provide estimates of the errors involved in measuring poverty using a “total error” approach.<sup>8</sup> In doing so the Bank should evaluate the sources and magnitudes of error, “particularly nonsampling error and the error introduced by the process of determining the” dollar-a-day (hereafter DAD) poverty line (Atkinson, 2016, p.50).<sup>9</sup>

In the present exercise we estimate the global aggregates on poverty, replicating the World Bank’s DAD method, while extending it within a Monte Carlo framework to estimate their margins of error. This implies that both iPL and global poverty rates are hereafter considered as stochastic variables. In addition, we operationalize one more of the Commission on Global Poverty recommendations—number 15—that urges the Bank to utilize a cost of basic needs (CBN) method as an alternative global poverty indicator.<sup>10</sup> We compare the two methods in terms of the

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<sup>5</sup>The World Bank also functions as the UN custodian institution for monitoring global poverty.

<sup>6</sup>[http://www5.worldbank.org/mdgs/poverty\\_hunger.html](http://www5.worldbank.org/mdgs/poverty_hunger.html), last accessed October 31, 2017.

<sup>7</sup>On September 18, 2018 the World Bank published the global poverty estimates for 2015 (the latest year for which a global estimate is available).

<sup>8</sup>Recommendation 5: “The World Bank poverty estimates should be based on a “total error” approach, evaluating the possible sources, and magnitude, of error, particularly nonsampling error and the error introduced by the process of determining the International Poverty Line” (Atkinson, 2016, p.50)

<sup>9</sup>It should be noted that despite the long line of criticism on the Bank’s global poverty measurement methodology (Deaton, 2010a; Reddy and Pogge, 2010; Srinivasan, 2009; Subramanian, 2015; Moatsos, 2017a), the point regarding the missing error terms has not been raised as much as its importance in monitoring the evolution of global poverty entails.

<sup>10</sup>Recommendation 15: “The World Bank should develop a program of work, in conjunction with other international agencies, on a basic needs–based estimate of extreme poverty; these estimates would, when developed, form an alternative indicator to be included in the portfolio of Complementary Indicators, and serve to provide an interpretation of what the International Poverty Line would

size of their estimates' error terms, and in terms of the confidence level at which the global poverty rate in 2015 is half that of 1990, and, further, we investigate the percentage of poverty reduction that took place between 1990-2015 for each of the methods at a 95% confidence level. In doing so we come to the unfortunate conclusion that none of the two methods provides evidence in support of MDG1's success at a 95% confidence level. The CBN method shows that the world has come slightly over half-way in halving global poverty during the 1990-2015 period at 95% confidence level<sup>11</sup>, while at the same confidence level DAD method identifies no reduction in global poverty. This very surprising finding is attributed exclusively to the iPL's derivation method, particularly the averaging step in the DAD method (see section 4.2 for details).<sup>12</sup>

Overall, the DAD method demonstrates considerably higher relative standard deviation compared to those of the CBN approach.<sup>13</sup> As our findings suggest that the bulk of the DAD uncertainty stems from an averaging step in the identification of iPL, this in turn implies that the main driver behind the increased uncertainty lies with the rather vague poverty concept encapsulated in the DAD method, as it draws upon varying governmental standards among some of the poorer countries around the globe without, for example, further analyzing the nature of those varying standards. Essentially, the international Poverty Line (iPL) of the DAD method is defined as the simple average of some national poverty lines (NPL) expressed in international dollars.<sup>14</sup> Consequently, as the values of the NPLs—used to estimate the iPL—vary considerably, their average value also has a wide confidence interval that propagates into the final global poverty rates estimates. Additionally, an important, yet secondary, source of uncertainty stems from the purchasing power parity (PPP) exchange rates which are used in the DAD methodology to convert local currency to international dollars.

For the CBN approach we account for uncertainty on two main aspects which the DAD approach does not consider: (a) anthropometric measurements that de-

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buy.” (Atkinson, 2016, p.xxi). The World Bank decided not to pursue with the implementation of this recommendation.

<sup>11</sup>Do note that strictly speaking one cannot investigate the success of MDG1 using a CBN method, since MDG1 is formulated in DAD terms as it uses a dollarized poverty line—which also happens to be the iPL obtained via the DAD method. However, one can investigate whether some CBN based poverty rate—that is largely comparable to the DAD at one point—has been halved during the MDG1 period (see sections 4.2 and 4.3 for more details). See sections 4.2.4 and 4.3.4 for more details and the constraints of this investigation.

<sup>12</sup>Ignoring the uncertainty stemming from this averaging step results in MDG1 success at more than 95% confidence level (see section 4.3 for details).

<sup>13</sup>The DAD implementation with the most complete consideration of error sources has about 4.5 times higher relative standard deviation, compared to the CBN complete implementation. See the results section and figure 4.5 in particular.

<sup>14</sup>The countries for which the NPLs are averaged are dubbed as the *reference group*.

fine the poverty lines' nutritional requirements, and (b) uncertainty concerning the prices and the budget shares of the consumption basket components.

Finally, for both DAD and CBN methods we broadly account for the uncertainty of the consumption (or income) distributions used in the calculations, the uncertainty regarding the imputed poverty rates for countries without data, and the uncertainty introduced when using a consumption (or income) distribution from another year when there is none available for the years of interest.<sup>15</sup> Compared to the error sources described above, these uncertainties play a very small part in the overall confidence interval of the global poverty rates, and the lack of available data to accurately account for their actual distributions should not be alarming.<sup>16</sup> In any case, our main results obtain even when ignoring those error sources common to both methods.<sup>17</sup>

## 4.2. Materials and Methods

### 4.2.1 Dollar-a-day Poverty Lines

This approach has been developed by World Bank researchers over a long period since 1991 (Ravallion et al., 1991a; Chen and Ravallion, 2001; Ravallion et al., 2009; Ferreira et al., 2015), and its core conceptual origin can be traced further back to 1979 in Ahluwalia et al. (1979) who seems to be the among the first to use PPP exchange rates in international poverty estimates. Ravallion et al. (1991a) replaced the Indian poverty line used by Ahluwalia et al., (ibid), with the nearest round number of a small cluster of NPLs expressed in PPP dollars. That number being relatively close to one dollar (in 1985 prices) gave birth to the "dollar-a-day" method. When the 2005 ICP PPP rates became available, Ravallion et al. (2009, hereafter RCS) provided an update of the iPL estimate using the average of NPLs from the 15 countries with per capita consumption of less than \$60 per day in 2005 PPP dollars. This group of 15 countries constitutes a core concept in the DAD methodology and it is dubbed as the *reference group*.

Ferreira et al. (Ferreira et al., 2015, hereafter FEA) update the iPL to the 2011 PPPs. However, FEA do not repeat the entire procedure that RCS specify, and decide instead to use the same 15 countries used in RCS. This makes the current

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<sup>15</sup>Distribution of consumption is preferable to that of income also according to the World Bank and the Commission's Report Atkinson (2016), this is why an income distribution is only used when the distribution of consumption is not available.

<sup>16</sup>It is only when assuming extremely wide distributions for these parameters that they appear to have an identifiable impact on the final estimates, but not on our conclusions.

<sup>17</sup>See rows with ID 1 in tables 4.3 and 4.4.

iPL a hybrid PPP-based global poverty line.<sup>18,19</sup>

In what follows we review the key points of the DAD method, and distinguish key steps that operate as uncertainty entry points. In that respect, our contribution to the DAD method is threefold: (a) we introduce key elements of uncertainty, (b) we add an omitted consistency criterion (see below for details), and (c) we implement a solution within the spirit of the original approach for the frequent cases of PPP draws that the original method does not provide consistent solutions in determining the iPL.

The procedure that produces the iPL builds on the relation between NPLs and consumption per month (see also figure 4.3). To that end RCS use the following equation:

$$Z_i = Z^*I_i + f(C_i)(1 - I_i) + \varepsilon_i \quad (4.1)$$

where  $Z_i$  is the poverty line in country  $i$ ,  $Z^*$  is the average NPL of the reference group,  $I_i$  is one if country  $i$  is in the reference group and zero otherwise, and  $f(C_i)$  is a function of consumption per capita per month  $C_i$ . Function  $f(C_i)$  is later defined and fitted as a linear function of  $C_i$ . The estimated version of equation 4.1, as it appears in RCS<sup>20</sup>, is as follows:

$$\begin{aligned} Z_i = & 37.983I_i & + (19.388 & + 0.326C_i)(1 - I_i) & + \hat{\varepsilon}_i \\ & (12.55) & (2.99) & (11.15) & \\ R^2 = & 0.890 & , & n = 74. & \end{aligned} \quad (4.2)$$

The decision to split the group of countries, and attempt an elbow fitting to the data,<sup>21</sup> is made on the basis that the iPL capturing absolute poverty levels would be around the minimum NPL among the countries with low consumption per capita.<sup>22</sup>

<sup>18</sup>Since FEA do not use the 2011 PPPs for establishing the separation threshold of the reference group, they indirectly use the 2005 PPPs as they take that part of the DAD process directly from the RCS treatment.

<sup>19</sup>We follow FEA and World Bank's PovcalNet in working with the 2005 PPP exchange rates and the 1.25\$-a-day in 2005 prices for a small set of countries. Those countries are: Bangladesh, Cabo Verde, Cambodia, Egypt, Iraq, Jordan, Lao PDR, and Yemen. FEA explain this choice on the basis of the discrepancy between the on site experience and the poverty estimates that the 2011 ICP based iPL provides. This correction is also applied in the CBN method for comparability purposes.

<sup>20</sup>In parenthesis are provided t-ratios based on robust standard errors.

<sup>21</sup>Meaning fitting the data with two consecutive regression lines where a kink is created in their junction. In this particular case the first line is a horizontal one. See also figure 4.3, but do note that the figure is log-normal, thus the second straight line is shown as a curve. This procedure is also known as a piecewise fit.

<sup>22</sup>In more detail, they argue that for the countries with the lowest consumption per capita per month the estimated poverty line when using the entire sample is lower than the average poverty line for that group. Put differently, the fitted line of a regression that considers the entire dataset gives a

At the same time, they argue that simply taking only the poverty line of the country with the lowest consumption, and use it as the iPL, will make the method prone to measurement errors at the country level. Based on these observations they turn to an averaging of the NPLs from a group of least consumption affluent countries, which is achieved by constraining the first part of the elbow fit to have zero gradient. As RCS put it: “there are measurement errors and methodological differences between countries in how poverty lines are constructed, which can be interpreted as noise in the mapping from the underlying welfare space into the income space.” Thus, averaging is an attempt to avoid country specific errors. Naturally this attempt, as any averaging, comes with an error in the estimate of the average that needs to be propagated into the global poverty rate estimates (Bailer-Jones, 2017, section 2.8).

The consequent issue is how to decide where the reference group threshold should be. RCS set two criteria for this: (a) the continuity criterion that requires  $Z^* = f(C^*)$  at the threshold, where the elbow’s kink is also located, and (b) the consistency criterion that requires  $C_i < C^*$  for all countries  $i$  in the reference group. Since  $f(C)$  and  $Z^*$  are estimated from the data they can be used to determine the threshold level by enforcing the continuity criterion (a). Next RCS test if for the resulting  $C^*$  consistency criterion (b) holds as well. Then RCS choose the threshold to be at \$60 that gets 15 countries in the reference group, since, as they report, taking the 10 or 20 poorest countries produces “not consistent reference groups, unlike that defined by the poorest 15 countries”.

In some of our implementations<sup>23</sup> we add one consistency criterion to the two above, that stems from the trivial observation that for a threshold to be consistent it should in addition hold that (c) for any country  $j$  not in the reference group  $C_j > C^*$ . Intuitively, the need for this criterion is similar to the need behind criterion (b). Criterion (b) is required to assure that the fitted line in the non-reference group will not have a gradient that makes its fitted line intersect with the fitted horizontal line of the reference group below the  $C^*$  consumption level (see also the–lognormal–figure 4.3 for an overview). Likewise, criterion (c) is required to guarantee that the intersection of these lines will not happen at a location above the consumption level of any country not belonging to the reference group. Only when taken together the three criteria above guarantee that the gradient of the second fitted line of the elbow is such that their intersection will happen within the consumption per capita area

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lower estimate for poverty at the lowest level of consumption found in the sample. RCS found this identification as non-satisfactory.

<sup>23</sup>Referring to IDs 4-6 in table 4.3.

between reference and non-reference countries.<sup>24</sup>

For the frequent occasions that the solutions are inconsistent, a defensible alternative—in line with the spirit in the RCS approach—is required. Such an alternative is provided by using as the reference group the set of countries for which the residual sum of squares of the elbow fitting is minimized. This idea lies behind the Hansen (2000) method that RCS use as well (see previous footnote). Therefore we posit that it is within the spirit of their approach. Due to the sensitivity of the method to PPP changes<sup>25</sup> in about 30% of the iterations the solutions were inconsistent and this alternative was applied.<sup>26</sup>

In addition to the uncertainty introduced by the estimation method of iPL (whose key operation seems to be the averaging of NPLs), we investigate the influence that uncertainty of the PPP exchange rates brings about to the identification of the threshold for the reference group. To do so we conduct a Monte Carlo pseudo-experiment in which the PPP exchange rates for both 2005 and 2011 are chosen from a normal distribution around the mean PPP rate for each country using their respective error terms (see section 4.2.5 below for details on data sources).

Arguably a more consistent application of the dollar-a-day methodology would be to redo the methodology in 2011 PPP rates altogether, both for the threshold selection and the averaging of NPLs. However, we are interested in comparing the Dollar-a-Day poverty line methodology as it is applied by the World Bank for monitoring MDG1. Thus we constrain ourselves in replicating the methodology as described in FEA, with the additions of the treatment of inconsistencies described above when this is required, and the Monte Carlo pseudo-experiments to account for error propagation.

Overall, we observe that the DAD method accumulates part of its uncertainty from the uncertainty in the PPP rates due to the following reasons: First, with respect to the consumption per month threshold for inclusion in the reference group. From this implication the set of countries of which the NPLs are averaged to produce the iPL would change as well. Second, the consumption level of each country when expressed in PPP dollars. Third, the level of an NPL with respect to other countries' NPLs. Fourth, with respect to the consistency of the threshold selection. Fifth, by the relative differences among the PPP rates of countries included in the iPL, and those not included. This last point affects the relative mean value of the distribution of each country out of the reference group relative to those in the group.

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<sup>24</sup>As a final step RCS verify their result with a constraint version of the method proposed by Hansen (2000). We do not follow this final step here since it becomes apparent that if the three criteria above cannot be met, then the solution from Hansen will also not be consistent.

<sup>25</sup>See the subsection 4.3.1 in the results for more details.

<sup>26</sup>Note, however, that the results and conclusions also obtain without the use of this treatment, see table 4.3 rows ID 1-3 & 7.



It is worth noting that these PPP exchange rate error sources demonstrate rather moderate variability, while the main source of error in defining the iPL stems from the requirement of the DAD method to take an average of a group of NPLs.<sup>27</sup>

## 4.2.2 Cost of Basic Needs Poverty Lines

The definition of poverty that we operationalize here falls between two definitions found in international treaties. The upper bound in terms of direct costs can be found in the Copenhagen Declaration by the United Nations: “[a]bsolute poverty is a condition characterized by severe deprivation of basic human needs, including food, safe drinking water, sanitation facilities, health, shelter, education and information. It depends not only on income but also on access to social services.”<sup>28</sup> The lower bound can be found in article 25 of the Universal Declaration of Human Rights. Pogge (2011, p.2) uses this article for a defensible definition of poverty, as a condition in which someone lacks: “a standard of living adequate for the health and well-being of himself and of his family, including food, clothing, housing and medical care.”<sup>29</sup>

The composition of the CBN poverty lines rests on two building blocks, as shown in table 4.1. The upper block, consists of the food component, and the lower block of non-food expenses (separated by a bold line). The food component builds on the bare bones basket concept introduced by Bob Allen (2001, 2013) in estimating welfare ratios and real wages historically, as well as poverty lines contemporary (Allen, 2017). The quantities used on each food source are such that the global poverty rate for 2015 is comparable with the World Bank’s point estimate according to the most complete treatment of the DAD error sources.<sup>30</sup> This choice is motivated by the observation that higher DAD poverty lines show less appealing poverty reduction, since their downward trend is slower (Chen and Ravallion, 2010, p.1619, table VIII).<sup>31</sup> We wish to avoid such a comparability problem that could arise if a CBN-based global poverty rate would be much higher or much lower than the DAD. Constrained by this methodological consideration our implementation of the aforementioned definitions becomes a frugal one, as shown in table 4.1.<sup>32</sup>

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<sup>27</sup>Observe the quadrupling of the confidence interval in the iPL when considering the averaging and when not, as shown in figure 4.5.

<sup>28</sup>Obtained from <http://www.un.org/documents/ga/conf166/aconf166-9.htm> on February 22nd, 2016. The requirement for the provision of access to social services is silent in our implementation.

<sup>29</sup>Universal Declaration of Human Rights, G.A. Res. 217 (III)A, art. 25, U.N. Doc. A/RES.217(III) (Dec. 10, 1948).

<sup>30</sup>Referring to row ID 4 in table 4.3

<sup>31</sup>See also figure 4.4 in the results section.

<sup>32</sup>Otherwise, other more demanding CBN configurations could have been operationalized here, more similar to those discussed in Allen (2017).

Do note that we take the mean of 3 cheapest food bundles as a technical way to introduce some minimal dietary variety, thus no uncertainty stemming from this step is considered.

Table 4.1: The yearly cost of basic needs consumption basket.

Item	Units	Basic Needs Basket	SD (%)***
Energy Target	kcal/day	MDER	****
Protein Target	kcal/day	0.75 gr/kg	16.2
Minimization	-	mean of 3 cheapest bundles	none
Meat or fish	kg/year	8 or 16*	-
Butter or oil or ghee	kg/year	8	-
Sugar	kg/year	5	-
Main staple(s)	kg/year	based on kcal/protein target (estimated as a residual of the above)	-
Clothing and Footwear	%	budget shares**	16
Water	%	budget shares**	65
Energy	%	budget shares**	20
Housing	%	budget shares**	22
Health	%	budget shares**	39
Education	%	budget shares**	52

\* : 8kg of meat or 16 kg of fish, whichever is cheaper.

\*\* : The budget shares are available from World Bank's Global Consumption database. See section 4.2.5 for more details.

\*\*\* : For the discussion of the standard deviations (SD) of nutrient targets, food quantities and budget shares shown here see section 4.2.5.

\*\*\*\* : Depends on the country demographic profile and other parameters as discussed in section 4.2.5.

The non-food component uses the budget shares of expenditure categories that are relevant to the aforementioned poverty definitions (as shown in table 4.1). The cheapest bundles that satisfy the recipe shown are identified using linear programming, thus accounting for substitution effects by those living in conditions of poverty, and the solution in the main staple may contain more than one products. This means that the consumption basket is not held fixed in its composition, rather it is a goal oriented basket that achieves a certain level of welfare broadly in line with the aforementioned definitions of poverty. The total amount of basic nutrients (calories and proteins) that the food component should contain is calculated using the FAO (2001) methodology for Minimum Dietary Energy Requirement (MDER). Accordingly, the calories required per day are estimated via the MDER, and the proteins as a linear function of the population weighted average body weight derived in the MDER calculations with a proportion of 0.75 gr of protein per kg of weight (World Health Organization, 1985, sec.8.2.2). Section 4.2.5 discusses the various uncertainties shown in table I.

### 4.2.3 Uncertainties common to both methods

There are two important methodological choices that the dollar-a-day and the cost of basic needs approach have in common.

The first one concerns the use of sparse distributional data. In order to achieve a satisfactory population coverage, the World Bank re-uses the available consumption or income distributions outside of their year of origin. For comparability, we follow this approach of the Bank as detailed in Chen and Ravallion (2010, 2004) and Ferreira et al. (2015). To extrapolate the distribution to a different year a relevant variable from national account statistics (NAS) is used to estimate the mean of the distribution, while the shape of the distribution remains unchanged.<sup>33</sup> Preference is given to real growth in household final consumption expenditure from the NAS, and, when that is not available, the fall-back option is to use real GDP per capita growth. The main empirical issue with this method is that there is a divergence among the “organic” growth rates between consecutive household surveys (HHS) and the growth from NAS (Deaton, 2005, p.2). To account for this discrepancy between HHS and NAS growth we follow the method applied by FEA. It uses an 87% multiplier as an adjustment factor between NAS and HHS growth rates to all countries, with only two exceptions: for India the correction factor is 51% and for China 72%.<sup>34</sup>

The second important methodological choice, that the two methods have in common, concerns the treatment of countries without sufficient data to estimate their poverty rates. In such situations the World Bank opts to impute poverty rates for the countries without data with the average regional poverty. The implicit assumption claims that countries which have (or manage to somehow acquire) the means to monitor poverty are a good proxy for poverty levels in countries that don't. This is a rather strong assumption that one would like to account for. A simple method is to add a normally distributed error term each time such an imputation is made and markup the regional average by a fixed percentage, simply to keep track of possible error that enters the estimation.<sup>35</sup>

In addition, do note that both methods exclude the developed countries. Fortunately, for investigating the success of MDG1 this is appropriate, as the developing

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<sup>33</sup>For years between two available distributions their (time) weighted average is used.

<sup>34</sup>Although this adjustment is a welcomed correction towards the right direction, it is not in itself error less. However, we choose to ignore this source of error in the present treatment, as more straightforward addressable and important sources of error are considered. Further, since this source of error is common for the two methods that we compare, our choice bears no cost in this respect, but in all likelihood this translates to an underestimation of the "total error".

<sup>35</sup>The exact values used are shown in the caption of table 4.3 in the results; all implementations but the first apply this method. As the baseline implementation (ID1) shows, our conclusions are not dependent on the exact value or even the consideration of this parameter.

world is the reference domain of MDG1.<sup>36</sup> Finally, the measurement error and the incomplete measurement of consumption (or income, if income distribution is used) is accounted for by a normally distributed error term.<sup>37</sup>

#### 4.2.4 Error Propagation in Monte Carlo Simulations

##### DAD simulations

Table 4.2 expands the table of nonsampling errors from Atkinson (2016) and provides an overview of the sources treated here and how. Clearly we do not account for all the possible sources of error, but we do account for the majority to a certain extent.

With respect to the DAD method, as discussed above, the main sources of error—which are specific to this method—that we account for are: (1) the averaging of NPLs, and (2) the underlying uncertainty in the PPP exchange rates. There are five main implications with respect to the role of PPP uncertainty: (a) The consumption per month threshold for selecting the countries in the reference group changes. (b) The relative and absolute consumption per month levels change; (c) The relative value of an NPL changes with respect to other countries; (d) The composition of the reference group selection procedure is affected, and, as we show in the supplementary text, in about a third of our draws the threshold separating the reference group from the remaining NPLs is not consistent; (e) The relative value of the currencies within the reference group as opposed to those outside of that group, making the resulting iPL relatively more or less expensive to the countries outside of the reference group.

Do note that these implications are intertwined and cannot be treated in isolation. Therefore at each PPP draw the entire set of steps of the DAD method needs to be repeated to estimate the PPP-draw specific iPL. In turn this implies that there exists an unknown true value of the iPL that needs to be estimated separately for each year. Ideally if a new set of PPPs were calculated for each year this would probably be what the World Bank would be doing, judging from its reaction to re-estimate the iPL after each new ICP round. The DAD method is expected to maintain welfare equivalence among PPP rounds, therefore any incompatibilities between the iPL of different PPP sets should not be seen as a problem in our estimation of uncertainty, but rather as an issue that the DAD method may have to

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<sup>36</sup>For comparability we keep the same definition for developing countries with the World Bank. If the country was a developing one in 2005 it is included for both 1990 and 2015 regardless of its actual development status at those benchmark years.

<sup>37</sup>See table 4.2 and next section for more details. As shown in table 4.3, again our results obtain even without this—reasonable but rather arbitrary in its nature—consideration, while its impact is very marginal when applied.

Table 4.2: “Illustrative Checklist for Nonsampling Errors”, details added upon the original (Atkinson, 2016, p.52)

	Source of error	Accounted for in	Approach/Comment
1	Incomplete country coverage	Both	Add normally distributed error terms on those regional averages plus a fixed % addition upon that average.
2	Incomplete measurement of consumption/measurement error	Both	A crude 5% standard deviation applied to all distributions.
3	Use of income in place of consumption	None	Consumption is arguably a better indicator of welfare than income, but not all countries have consumption HHS.
4	Population missing from sampling frame	None	E.g. those incarcerated.
5	Survey differential nonresponse	None	Under-reporting by the rich and under-representation of the poor.
6	Inaccurate or out-of-date population totals	None	-
7	Errors in the determination of the poverty line	Both	Various uncertainties (PAL, MDER, NPL averaging, PPP, etc, see text for details).
8	Standard error of PPP indexes to calculate baseline local currency poverty line	DAD	Estimated PPP standard errors and its impact on iPL determination. This is not applicable to CBN.
9	Surveys not comparable over time	None	E.g. due to methodological changes.
10	Extrapolation of out-of-date survey data	Both	A correction is applied based on the history of HHS and NAS growth rates.
11	Bias in domestic CPI to update local currency poverty line	CBN	This is encapsulated in the CBN approach.
12	Differential inflation for the poor	CBN	The consumption baskets used in CBN are CPIs for the extreme poor.
13	Rural/Urban and other geographical differences	Both	Rural/Urban split for the countries with available data, namely: China, India and Indonesia.
14	Use of equivalence scale in place of per capita calculation	None	Access to the HHS microdata is required for addressing this. On the required scale only World Bank researchers have the required access.

attend to. By adding the PPP uncertainties, our approach—in addition to estimating the confidence interval—partially simulates the behavior of yearly updating the iPL.

To investigate the effect that the aforementioned sources of error have on the size of the uncertainty of the global poverty estimates, all those points (along with the methodological choices that both methods have in common) are accounted for through each iteration in the Monte Carlo procedure. The flow chart of figure 4.1 depicts how the flow of calculation and the points where draws are taken from the underlying distributions.

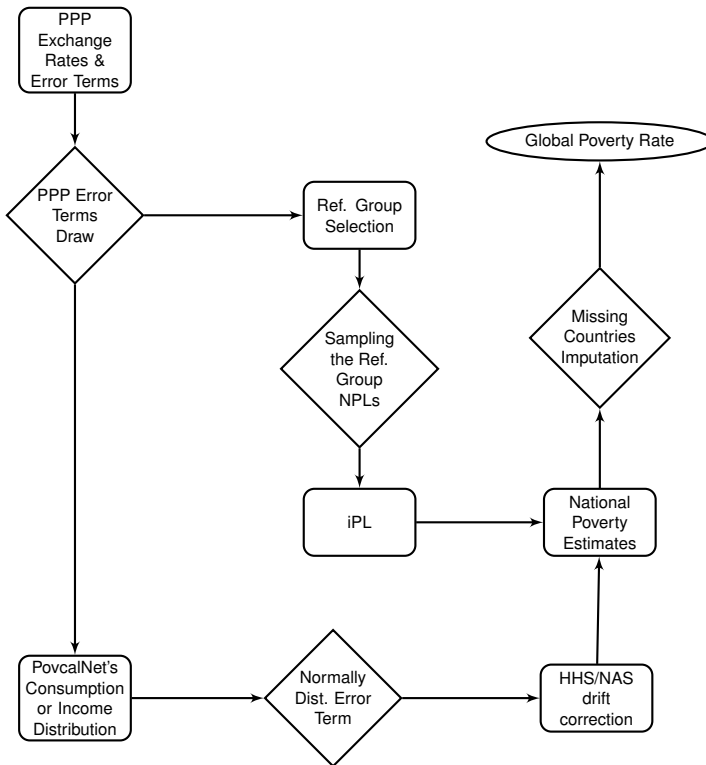


Figure 4.1: Architecture of Data and Monte Carlo method for the DAD method. Diamond shaped objects mark a draw from a distribution in the Monte Carlo simulation.

As a new set of PPP exchange rates is drawn on each iteration, the entire set of consumption per month, the countries in the reference group, the NPLs, and consequently the iPL, and the distributional data are re-calculated using those new rates. In turn, they are used for the estimation of one global poverty rate corresponding to that PPP draw following the procedure as described in FEA in great detail and

qualified in the above section detailing the DAD method.

Overall, changes in PPP conversion factors affect what the conversion of nominal terms to (internationally comparative) “real terms” means, so errors arising from changes in the PPPs do pertain to the exercise of estimating the iPL for any year, and obviously for the 2011 ICP reference year. However, one might object that although the diamond “PPP Error Terms Draw” of figure 4.1 is part and parcel of the uncertainty estimation, a subsequent re-selection of the reference group is not (shown as the parallelogram “Ref. Group Selection” in the same figure). Such reasoning assumes that once the set of reference countries has been decided it must be left untouched and constant in the estimation of the procedure’s uncertainty. Nonetheless, this reasoning would ignore the fact that PPP fluctuation recasts the relative values of the group of countries with low consumption thus re-ranking the countries and in addition the splitting of the groups into a reference and a non-reference group may not be consistent any more. As a consequence the whole DAD procedure needs to be repeated both for consistency, and in order to actually follow the entire RCS specification procedure that the DAD approach prescribes for iPL.<sup>38</sup> Put simply, there is no \$60 (in 2011 PPP terms) threshold anymore as this has changed as a result of the PPPs fluctuations, therefore the whole procedure as depicted in figure 4.1 needs to be repeated from the beginning and in its entirety.

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### CBN simulation

Now turning to the CBN method, a range of key error sources are accounted for in our implementation as described in table 4.2 above and shown in the flow chart of figure 4.2. For each error source, treated with the Monte Carlo technique, values are drawn at random from the distributions around the mean value of each variable.

More specifically, and with respect to the price data, we use the standard deviation of prices from countries which report their prices from more than 3 distinct markets within the United Nations World Food Program price dataset. The value of this relative standard deviation is 21%, and we further assume that those prices follow a normal distribution. The error terms for the various consumption budget shares are derived from the data available in World Bank Global Consumption database, and the standard deviations are those shown on table 4.1 which are applied assuming normal distributions.<sup>40</sup> For the height data—which are necessary to

<sup>38</sup>See also section 4.3.1 for more details in the impact of PPP fluctuations.

<sup>39</sup>The procedure to arrive at an iPL by sampling the reference group’s NPLs corresponding to every PPP draw, instead of taking a simple average, has been discussed extensively in section 4.2.3 and in figure 4.1 is represented by the diamond “Sampling the ref group NPLs”.

<sup>40</sup>We focus on the data for the 3 countries that have sub-national data (India, Brazil and South Africa). This is done since we are interested in the within countries variance of the budget shares.

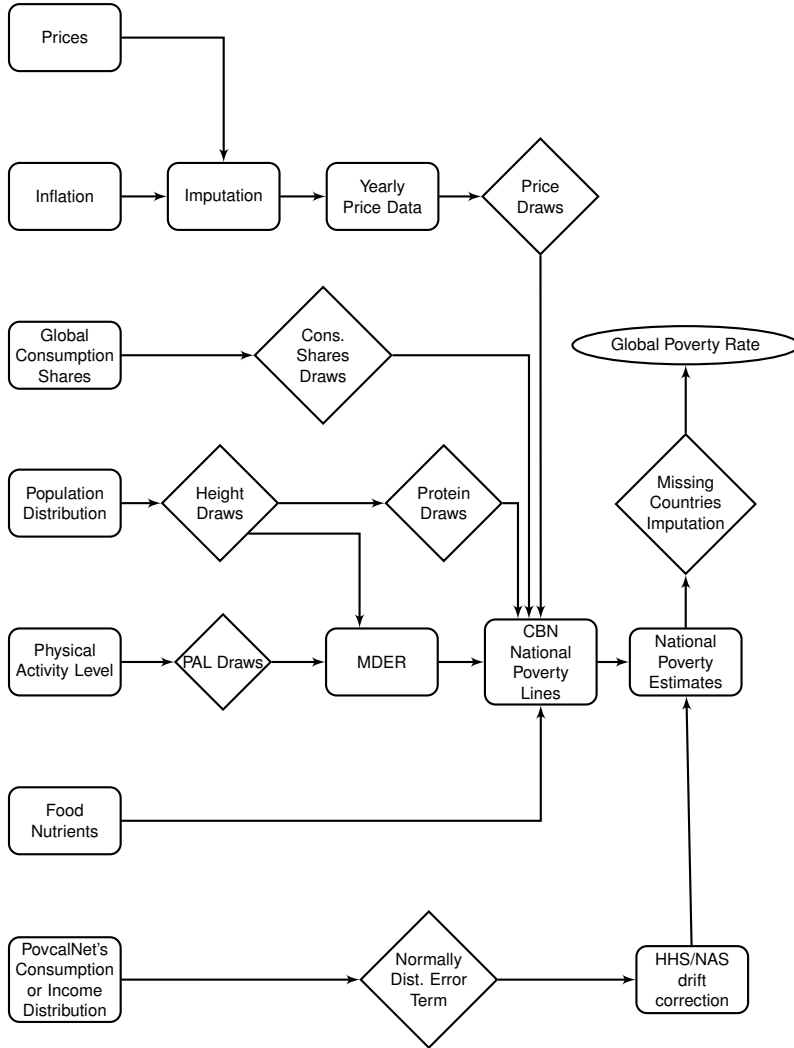


Figure 4.2: Architecture of Data and Monte Carlo method for the CBN method. Diamond shaped objects mark a draw from a distribution in the Monte Carlo simulation.



estimate the minimum caloric intake (MDER measured in kcal<sup>41</sup>) and the amount of proteins in grams—a uniform distribution around the mean with 3 cm radius is assumed for the cases with available height data, and 6 cm in cases when height data had to be imputed.<sup>42</sup>

For calculating the MDER and the protein intake we further need the physical activity level (PAL) of the population living in conditions of poverty. To this end we use a uniform distribution within the values that FAO categorizes as “active or moderately active lifestyle” (1.70-1.99) and “vigorous or vigorously active lifestyle” (2.00-2.40) (FAO, 2001, p.38, table 5.3).<sup>43</sup> In terms of PAL we therefore assume that the distribution and the implied uncertainty for those living in poverty is the same in all developing countries.

Further, table 16 in World Health Organization (1985) mentions that the pooled coefficient of variation of all listed studies in mean requirement of protein is 16.2%. We will use the same uncertainty for the 0.75 gr of protein per kg of weight that the report qualifies as appropriate, and we assume a normal distribution of this error term as well.

As Allen (2017) discusses in detail, there is substantial room for variation in both the choice of nutrient requirements and in the minimum values required for each in defining the food component in a CBN consumption basket. Opting for a more complex diet with additional minimum consumption targets for other nutrients would certainly lead our CBN global poverty rates results towards considerably higher values. As already discussed in section 4.2.2 above, we are concerned with the comparability of DAD and CBN poverty at least in one point in time, we choose a quite frugal consumption basket in order to obtain similar poverty rates in 2015 for both methods.

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Although we use normal distributions to draw values for those shares, the minimum and maximum observed in the sub-national data were respected, and draws outside those limits were recast.

<sup>41</sup>For further details about its calculation see FAO (2008), and Moatsos (2017a) for its use in poverty measurement.

<sup>42</sup>For countries without height data the regional average was used, and for countries with missing data the average growth from the region was used for data imputation. We recognize that this averaging may imply that we are using the same method as DAD does, albeit to a less key component of the CBN process than the step at which DAD uses averaging. However, do note that we do not produce a point estimate here, we simply attempt to roughly account for unknown height variables here by introducing reasonable guesses that are accompanied with considerable uncertainty; double when height data are unknown compared to the uncertainty in cases where height is known. This last step is entirely missing from the averaging in the DAD approach, and it is rather a key point of difference.

<sup>43</sup>Thus using a uniform distribution within 1.7 and 2.4, limits included.

### 4.2.5 Data

The anthropometric data we use are the age and gender population distributions from the United Nations World Population Prospects dataset United Nations (2015). The height data are taken from Baten and Blum (2015) which is the most complete dataset to date.<sup>44</sup> Price data are combined from the ILO's October Inquiry data, along with prices from the World Food Program (WFP) of the UN, and FAO data also from UN. Missing observations are filled in using the most appropriate available price index. Those are in order of preference: a food CPI for the poor which is available from ILO for some countries, an average CPI, or finally a price index that follows price volatility of similar products in the same country.<sup>45</sup> The composition in nutrients of the various food items is taken from the USDA database<sup>46</sup>, and retention rates are applied for caloric values following Appleton et al. (1999). Consumption shares used to account for expenses in clothing and footwear, energy, housing, health and education are taken from World Bank's Global Consumption Database.<sup>47</sup> The welfare distributions are those available at PovcalNet.<sup>48</sup> The average (population weighted) year of available HHS for 1990 is 1990.57 and for 2015 is 2013.93.

With respect to the estimation of the error terms in PPP exchange rates there are three available sources. Deaton and Dupriez (2011b) provide PPP error estimates that reflect sub-national sampling variability of PPP rates. The issue with such estimates is that if we were to use those we would also ought to include information about sub-national variation of income.<sup>49</sup> Fortunately the error estimates on PPP from a second source, Deaton (2012), do not reflect such sub-national information, but rather uncertainties due to variability in relative prices and expenditure

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<sup>44</sup>Dataset downloaded from the Clio Infra website, at <https://www.clio-infra.eu/>, last accessed April 15, 2018.

<sup>45</sup>For a more detailed discussion of these data sources see Moatsos (2017a).

<sup>46</sup><https://ndb.nal.usda.gov/ndb/>

<sup>47</sup>Data are available only for 2010. Last accessed on December 6th, 2016. The budget shares of the second consumption group marked as "Low" are used. Those are preferred over the "Lowest" consumption group since the food component of our basket is typically much lower than that in the "Lowest" consumption group. And since the budget shares of that group are lower than those of the "Low" group, using these budget shares would underestimate the threshold costs for those non-food components.

<sup>48</sup>Consumption based distributions when available, income based otherwise, as applied by the World Bank and FEA as well. Last accessed on October 3rd, 2018. The underlying distributions were retrieved from the World Bank using a slightly modified python script initially provided by Dykstra et al. (2014b). The retrieved distributional data are available in Moatsos (2018a) or directly at the Data Publication platform of Utrecht University.

<sup>49</sup>This is so since nominal expenditures and nominal income correlate positively and spatially with higher price levels within countries. Therefore sub-national covariance assumptions regarding income and price levels would be required.

patterns among countries. Deaton shows that the PPP rates of China and India have a relative standard error of 15%, with most of countries clustering at 15-17%. The potential issue with those estimates is that these estimates are work in progress, as part of a World Bank working paper, and they have not been duly refined to meet publication article standards.<sup>50</sup> Another potential issue would be the fact that Deaton (2012) provides PPP standard error estimates for the GDP PPP exchange rates and not the household final consumption PPPs that are used in global poverty estimates by the DAD methodology.

A third source, and the one that we use here, is provided by Rao et al. (2015) via the University of Queensland International Comparisons Database (UQICD) website.<sup>51</sup> Those estimates cover 181 countries and are provided for both 2011 and 2005 ICP rounds, while the two above sources only treat the 2005 ICP round. In addition they are available also for the PPP exchange rates related with the consumption GDP component, which is a concept closer to the required household final consumption PPP than those from GDP per se.<sup>52</sup> They are also less than half the errors estimated in Deaton (2012), with an average of 5.7% for 2005, making our analysis a conservative one with respect to the size of the PPP error terms. For the few countries that do not have an error estimate the average of the relative error terms of the developing countries is used. As a robustness check we experiment with half the PPP rates that Rao et al. (2015) provides and our conclusions remain unchanged.<sup>53</sup>

## 4.3. Results

### 4.3.1 Sensitivity of the DAD method to PPP rates

It is informative to first examine the sensitivity of the consumption threshold consistency—which separates the reference group from the rest of the countries in the DAD procedure—with respect to small differences in the PPP rates applied as the result of their standard deviations. Apparently even very slight changes in PPP rates, can give rise to an inconsistent threshold. This issue occurs in about a third of the draws in our simulations. It has been convincingly argued that the 1.9\$/a-day (in 2011 PPP terms) and the earlier 1.25\$/a-day (in 2005 PPP exchange rates)

<sup>50</sup>As Prof. Deaton has warned us in an email exchange.

<sup>51</sup><http://uqicd.economics.uq.edu.au/index.php>, last accessed April 10, 2018.

<sup>52</sup>The PPP rates here are those of “individual consumption expenditure by households”, which better represent the consumption of households than the generic PPP which are relevant for gross domestic product, and economy wide applications. Those are the PPP rates used by the World Bank’s PovcalNet as well.

<sup>53</sup>Based on this variation upon the complete scenario (ID 4 in table 4.3) this gives: MDG1 confidence level of 85% and a poverty reduction at 95% confidence level of 27.41%

were robust with respect to the various groupings of the least well off countries in terms of consumption per capita (see FEA and RCS respectively, also see Atkinson (2016) on the first point). However, a complication arises not with respect to the robustness of the average value of NPLs of the so chosen reference group<sup>54</sup>, but rather due to the frequency with which a PPP exchange rates draw fails the consistency checks of the DAD method.

Figure 4.3 shows the elbow fit using the PPP rates of PovcalNet, and provides identical conclusions as in RCS, suggesting a 1.9\$/a-day as the result of a consistent reference group selection. Let us consider the case of a small deviation from those PPP rates. In the case of Bulgaria's PPP rate it only takes a very modest 0.25% relative change to render the results reference group selection inconsistent (when the standard error for Bulgaria is estimated at around 3%).<sup>55</sup> The consistency breaks because of the  $C^*$  moving from slightly above the consumption per capita in the most affluent country in the reference group (Ghana), to slightly below it. Thus violating the consistency criterion (b) which requires that  $C_i < C^*$  for all countries in the reference group. If we were to simply remove Ghana from the reference group and recalculate the iPL with the 14 remaining NPLs we would face the same problem, as also in this case criterion (b) is violated<sup>56</sup>. We need to remove yet another country from the group (namely Nepal) to be consistent with criterion (b). However, in this case we will be violating consistency criterion (c), which requires that for any country  $j$  not in the reference group  $C_j > C^*$ , since there is a country (Nepal) not in the reference group that has consumption per capita lower than the  $C^*$ <sup>57</sup>. Tables 4.5 and 4.6 in the appendix provide the details of the aforementioned calculations. As table 4.6 in the appendix shows, any threshold selection would fail to separate the reference from the non-reference group with this PPP draw, since there is no country at which both criteria (b) and (c) are met.

As mentioned above, in total, around a third of the random PPP sets drawn based on the standard errors around the 2011 PPP exchange rates used by PovcalNet provide non-consistent separations of the two groups.<sup>58</sup> Regardless of the inclusion or exclusion of the inconsistent cases from calculations our results remain

<sup>54</sup>Observe in column DAD in tables 4.5 and 4.6 in the Appendix how little the dollar-a-day value of the iPL deviates from the original 1.25\$/a-day for a wide range of reference groups. One needs to double the size of the reference group to get a deviation of more than 6 cents, or approx. 5% in relative terms.

<sup>55</sup>The actual alternative PPP value used for Bulgaria in this example is 0.7352.

<sup>56</sup>See row 14 in table 4.6 in appendix, where  $C^*$  is 50.901 while consumption per month and per capita for the 14th country (Nepal) is 54.55, thus including Nepal in the reference group makes it inconsistent.

<sup>57</sup>See row 13 in table 4.6 in the appendix, where  $C^*$  is 54.676 while consumption per month and per capita for Nepal is 54.55, thus requiring Nepal to be included in the reference group.

<sup>58</sup>This bifurcation lies behind the spike toward the high end of the iPL distribution as presented in figure 4.5 below.

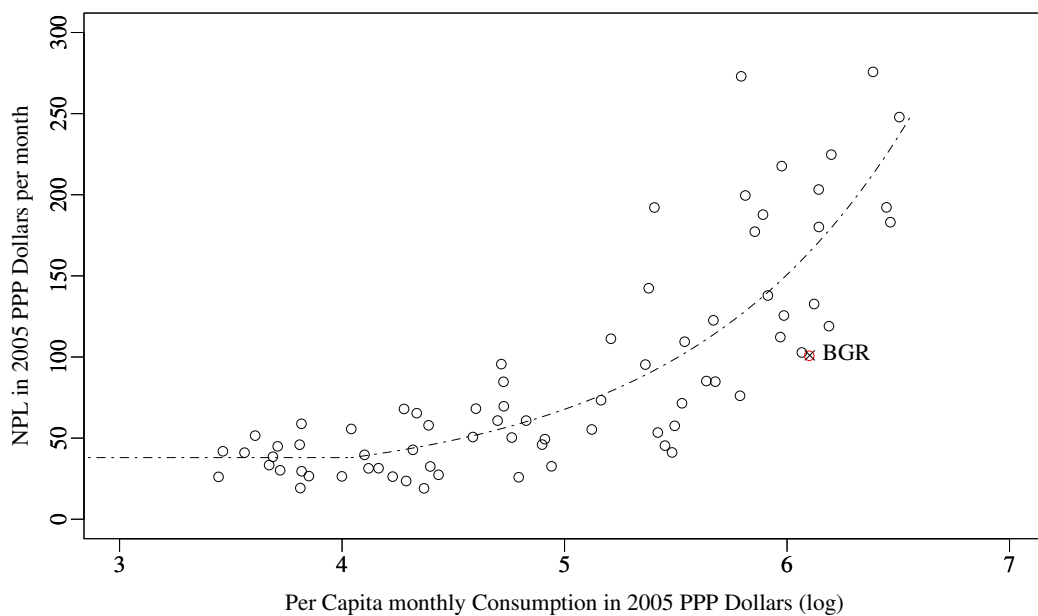


Figure 4.3: The elbow fitting of the National Poverty Lines as a function of log consumption per capita for the 74 countries in the RCS data set, using the Povcal-Net PPP exchange rates. Note that the upper line of the fit is log-linear. PPP rates for Bulgaria (BGR) are specially marked.

robust.

### 4.3.2 Sensitivity of Global Poverty Estimates to iPL changes

Figure 4.4 serves as a benchmark of how successful the replication of the PovcalNet methodology is in our implementation. Figure 4.4 contains four cases. The upper two refer to the year 1990 for which we compare our own calculations with those taken directly from probing the PovcalNet service with a sequence of iPL values<sup>59</sup>. The visible discrepancy between the two curves has an average deviation of 1.1% in relative, or 0.52 percentage points in absolute terms. Specifically at the standard 1.9\$/a-day iPL value the difference is 0.34 percentage points. This, rather small, discrepancy is most likely the result of two differences between our implementation and PovcalNet. For countries that do not have a survey during a benchmark year PovcalNet only uses a survey if it is available within a 2 years interval for global poverty estimates after 2010, and in a 3 years interval estimates for the 1981-2008 period (Ferreira et al., 2015, p.28). In our implementation we use a 4 years interval throughout, which allows us to include the 1993.5 household survey from India (in addition to the 1987.5 one), and be able to provide increased coverage for the 2015 estimate due to lack of surveys around that year.<sup>60</sup>

The other possible discrepancy is the difference in selecting the appropriate NAS growth statistic to be used in shifting the HHS mean to the benchmark year. Since PovcalNet does not report the exact NAS used at each individual case we cannot be certain in providing an exact replication of those choices. In light, however, of the uncertainties in the global poverty lines and rates presented in the results section we hold the position that the small deviations presented here do not undermine our results and conclusions, and that can be safely ignored.

The two lower lines, showing the comparison for 2015, are also very close for all iPL values, and at the 1.9\$ a day the difference is 0.72 percentage points and should be similarly attributed to the aforementioned causes (1.31 percentage points on average)<sup>61</sup>. This gap might be worrisome and even puzzling, however since this means that our point estimates between 1990 and 2015 are further apart than the estimates of the World Bank we are tentatively introducing a bias that works against our findings. We therefore remain confident with respect to the validity of our implementations and our conclusions.

<sup>59</sup>This is done with an updated version of the script initially provided by Dykstra et al. (2014b). The values we used are from 0.5 up to 5 PPP dollars with a 0.01 step.

<sup>60</sup>This increased coverage comes at a price in terms of HHS extrapolations; see section 4.2 for the methodological details.

<sup>61</sup>At the edges of the 95% confidence interval of the iPL, shown in table 4.3 at row ID 4 and in the upper sub-plot of figure 4.5, the difference is 0.29 and 1.68 percentage points, with a mean of 0.91 percentage points within the interval.

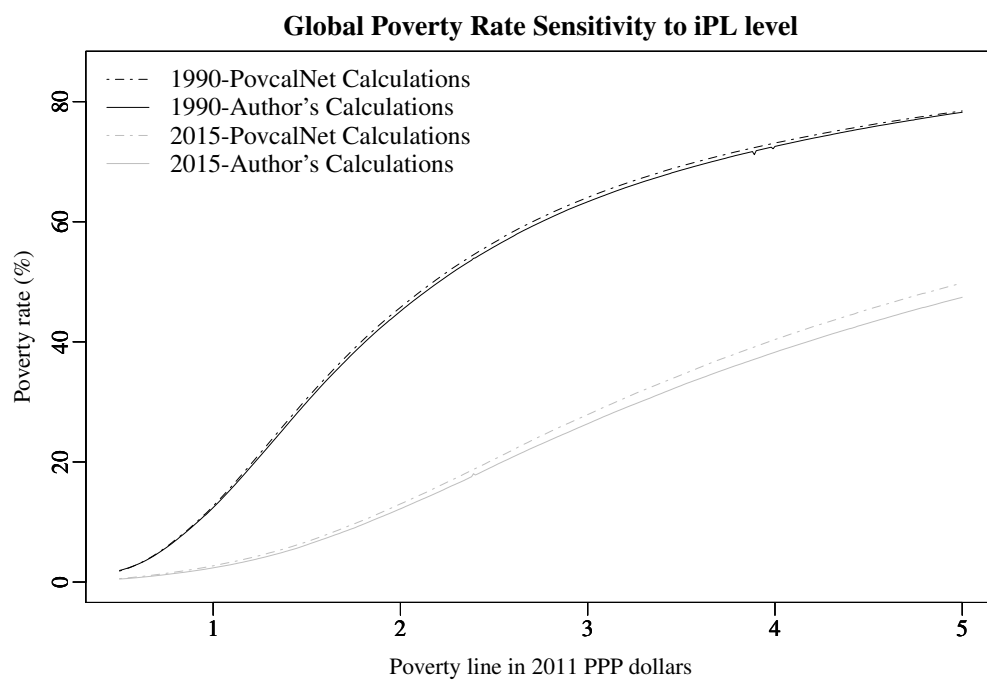


Figure 4.4: Sensitivity of global poverty estimates to iPL values.

### 4.3.3 Global Poverty Lines

The upper sub-plot in figure 4.5 shows two partially overlapping distributions of iPLs for the dollar-a-day approach.<sup>62</sup> The first and spiky distribution consists of the mean values of the NPLs from each reference group that results in each of the 10000 iterations of the Monte Carlo procedure. Methodologically it is a replication of the original RCS method, as extended for 2011 PPPs by FEA with two additional considerations<sup>63</sup>: The first concerns the treatment of the inconsistent reference groups. And the second is that at each iteration new randomly selected PPP rates for both 2005 and 2011 are used, based on their respective standard errors. This distribution of means shows how the iPL, computed as an average of NPLs of the reference group, varies with the variation of PPP rates. This approach merely propagates the uncertainty from PPP rates to the iPL estimate, and does not account for the uncertainties of the full DAD estimation procedure of the iPL.

The second distribution in figure 4.5's upper sub-plot is composed from a set of NPLs that are sampled at random, one at each iteration from the each time occurring reference group. After the 10000 iterations the distribution of those sampled NPLs is formed. Thereby simulating the overall distribution of reference group NPLs. The mean of this distribution is therefore an iPL estimate. The width of the distribution probes the uncertainty to the iPL estimate due to—not only to the PPP uncertainty—but also to the averaging of the reference group's NPLs. In effect, one could say that the average of the reference group NPLs is no better value for the iPL than any other value within the 95% confidence interval of this average distribution.

To elaborate on the rationale behind this point one needs to reconsider the reason for this averaging by RCS. The purpose of averaging in RCS is to cancel out measurement errors in NPLs. Independently of whether this actually works—and RCS do not discuss this point—it is a very natural way of selecting a typical NPL value from the reference group. However, when estimating the related uncertainty, we need to include information about the spread of the NPLs around their average. To be more explicit, imagine a situation where the NPLs of the reference group are almost perfectly aligned to each other, and therefore to their average value. This would certainly increase our confidence that the average is indeed the value that should be uniquely identified as the iPL. In the opposite scenario, of a reference

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<sup>62</sup>There is one issue of representation with respect to the x axis in the upper sub-plot of figure 4.5. Each PPP draw during the Monte Carlo procedure constitutes an entirely different set of PPP rates, which is not directly comparable with any other PPP set, as each of these PPP sets represents a different constellation of relative currency values. As such the values on the x axis cannot strictly be 2011 PPP Dollars. The implication is that we have to use a convention and rely on the term “fuzzy” to characterize the dollars of the 2011 ICP round. This bears no consequence on the results.

<sup>63</sup>We repeat those considerations here for clarity. See section 4.2 for more details.



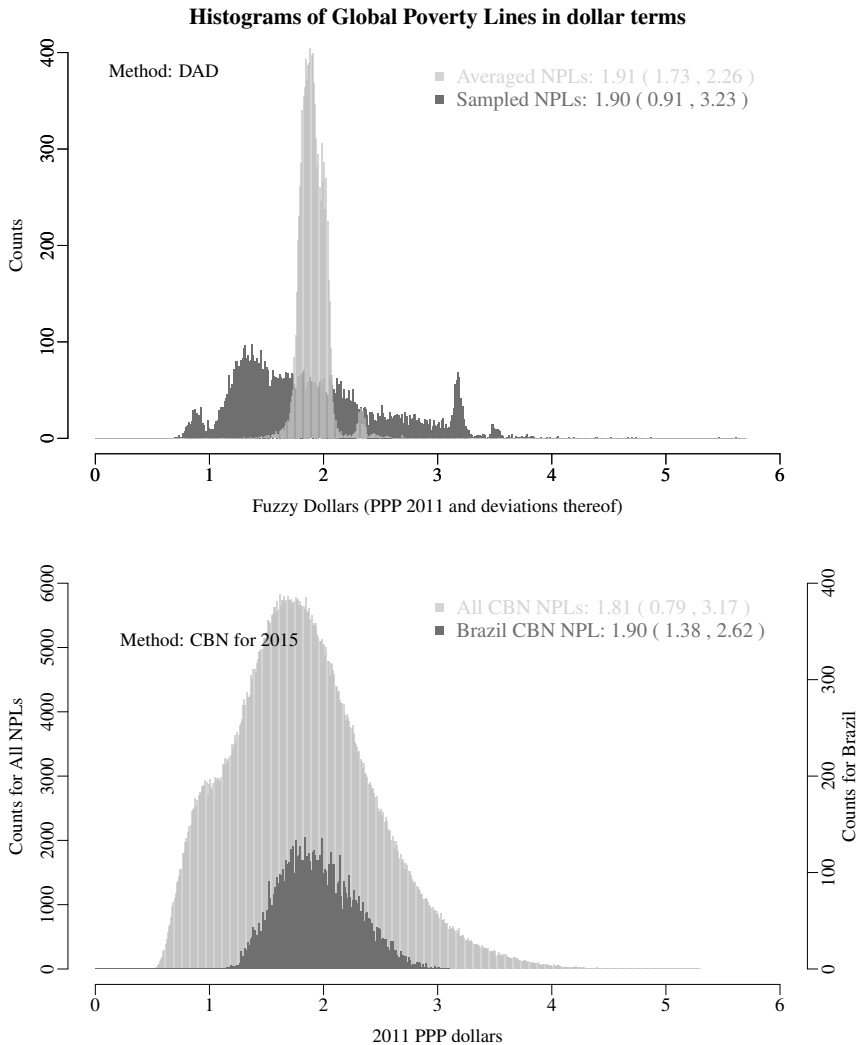


Figure 4.5: Histograms of Global Poverty Lines. Upper figure: includes all values of iPL, when PPP uncertainty is accounted for according to the complete implementation of (ID 4 in dark gray) and contrasted with the estimate iPL using same set of uncertainty considerations, but using the average iPL at each iteration (shown in gray) (see table 4.3 for the exact specifications, and the text for details regarding the fuzzy nature of this x axis see relevant footnote for its definition). Lower figure: the CBN based NPLs for 2015 expressed in PPP dollars for ease in exposition (in gray). For reference the NPLs calculated for Brazil are overlaid (in dark gray) using a separate y axis. The legend shows average values as well as the empirical 95% confidence interval.

group with wildly fluctuating NPLs around the same average value as before, we would be quite uncertain which value to choose as an iPL. However, if we only keep the average NPL for every PPP draw, the two scenarios are indistinguishable. We would like to retain this information - how spread are the NPLs inside the reference group at every draw. We therefore construct a simulated reference group by sampling one NPL for each PPP draw, and we consider this the distribution that describes the stochastic iPL.

Without taking a random sample at each iteration one severely restrains the uncertainties involved in the determination of the iPL. Hence, it is the width of this second distribution that is the required input to propagate the underlying uncertainties of the DAD method. Observe further that the breadth of the 95% confidence interval of the sampled NPLs is more than 4 times larger than that of the averaged NPLs, indicating that the uncertainty introduced in the process of averaging is the decisive source of error behind the wide confidence intervals of the global poverty estimates.<sup>64</sup>

In the lower sub-plot of figure 4.5 a similar graph this time for the CBN method is shown.<sup>65</sup> Overall the comparison of the wider distributions' breadth would lead one to conclude that similar error terms for the CBN based global poverty rates are to be expected. The important difference though is that in this distribution all poverty lines, for each of the countries for which we have available data to estimate poverty lines, are grouped together. Naturally those are not all applied on each and every country, as in the case of the DAD method. Rather, they are applied separately and only for the country for which they are constructed. To demonstrate the point we further show in the figure the distribution of the NPLs used specifically for Brazil.<sup>66</sup> This goal oriented tailoring of globally defined yet locally estimated NPLs appears to make a decisive difference in the size of the error term for the global poverty rates comparisons between the two methods.

#### 4.3.4 Testing for MDG1

The various Monte Carlo implementations are shown on table 4.3 concerning for the dollar-a-day method, numbered with IDs 1 to 7 in the first column. The first four implementations progressively account for additional sources of uncertainty, thus making the uncertainty estimate increasingly more complete. In the last three

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<sup>64</sup>As reported in table 4.3 in the next subsection.

<sup>65</sup>Note that in the CBN case there is no need for using the fuzzy dollars convention as all NPLs are calculated in local currencies and then converted to PPP dollars using the average rates for exhibition purposes only. The entire set of poverty estimates using the CBN approach is not using any version of PPP rates, and it is not exposed to the underlying PPP uncertainties, or the averaging process of constructing an iPL.

<sup>66</sup>Note that the distribution of NPLs for Brazil has a separate y axis to the right for reference.

Table 4.3: DAD Global Poverty estimates

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Impl. ID	Mean iPL	SD iPL	Mean 1990	SD 1990	Mean 2015	SD 2015	MDG1 Conf. Level (%)	Pov. Reduc. (%)
1	1.85	0.60	38.35	14.45	11.03	7.37	79	4.03
2	1.85	0.60	38.73	14.55	11.24	7.48	79	3.62
3	1.85	0.60	38.68	14.54	11.26	7.47	79	3.52
4	1.90	0.64	39.51	15.16	11.86	8.08	77	-
5	1.86	0.54	39.41	13.11	11.24	6.85	82	18.47
6	1.83	0.46	39.23	11.43	10.75	5.81	86	31.17
7	1.79	0.38	38.36	10.08	10.07	4.77	90	40.34
PCN	1.90	-	43.15*	-	11.62*	-	-	-

\*: World Bank PovcalNet estimates from

<http://iresearch.worldbank.org/PovcalNet/povDuplicateWB.aspx>, last visited on January 4th, 2019.

Configuration IDs: (1) baseline specifications with PPP standard deviations; (2) previous specification and a normally distributed error term of 10% and a 10% increase for the average of countries with data is added when imputing for countries with missing data; (3) previous specification and assume a 5% error in the mean of the income or consumption distribution; (4) previous specification and use the minimum sum of squares rule when consistency check fails in reference group selection; (5) previous specification and excluding the 1 lower and 1 higher NPLs from being randomly selected at the sampling procedure; (6) previous specification but excluding the 2 lower and 2 higher NPLs; (7) previous specification and the consistency check from implementation 4 is removed.

implementations the extent with which various sources of uncertainty are considered is reduced; those implementations serve as robustness checks. At the end of the table the official values of World Bank's PovcalNet are shown for reference (at the row labeled with PCN in first column). Columns 2-7 show the means and standard deviations for iPL, and global poverty rates estimates for 1990 and 2015. Column 8 shows the confidence level at which the MDG1 has been fulfilled, and the column 9 provides the poverty reduction achieved between the benchmark years, both at 95% confidence level.<sup>67</sup>

Implementation 1 provides the baseline estimations by only considering the PPP standard errors. With only this consideration, the confidence level for achieving MDG1 stands at 79% lower than the typical 95% or 90% confidence levels frequently used in social sciences. At the same time the poverty reduction between

<sup>67</sup>The achieved poverty reduction is calculated by estimating its maximum at 95% confidence level. The confidence level of MDG1 fulfillment is calculated by estimating the probability that a point from the 2015 distribution is lower than half of another point from the 1990 distribution, as required by the definition of MDG1.

1990 and 2015 at 95% confidence level stands as low as 4.03%.

In implementation 2 a normally distributed 10% standard error is added to account for the uncertainty in the imputation of poverty for countries without data<sup>68</sup>, it is also assumed that on average the poverty rate in countries without data will be somehow higher than those with data since they evidently show lack of capacity to monitor local poverty development. To simply account for this observation the regional average when imputing the poverty rate is increased by an arbitrary—yet moderate—10%. This term has a marginal impact on the results, by slightly increasing the poverty rates for both years and their respective standard deviation.<sup>69</sup> Implementation 3 adds a consideration for a 5% normally distributed error term in the mean value of the consumption (or income) distribution, which has a negligible impact.

ID4 is the most complete implementation with respect to the error sources considered, by adding a check for the consistency of the reference group in the DAD method. As detailed in section 4.2, when the PPP draw does not provide a consistent reference group selection we use the minimum sum of squares rule for selecting the reference group threshold.<sup>70</sup> This specification pushes the iPL average slightly upwards and widens its standard deviation. The confidence level of fulfilling MDG1 becomes 77%, and there is identifiable no poverty reduction at a 95% confidence level. This implementation is the one shown in the upper sub-plot of figure 4.6, and the wide overlap between the 1990 and 2015 distributions of global poverty rates is evident.

Beginning with the robustness checks, implementation 5 takes a conservative step and excludes the selection of the most extreme value at each iteration from the process of random sampling of the NPLs, which are used to construct the distribution of the iPL. This choice slightly reduces the SD for iPL and the poverty rates for both years. The confidence level of achieving MDG1 stands at 82%, while the identified poverty reduction at 95% confidence level rises considerably at 18.47%. Implementation 6 extends the exclusion of extreme values to two, and this pushes down the uncertainty in the estimates even further. The confidence level of achieving MDG1 rises to 86% and the identified poverty reduction increases to

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<sup>68</sup>The World Bank uses the simple average of the regional poverty rate to impute the poverty rate for countries without enough data to estimate the poverty rate. See the materials and methods section for more details in support of our simple uncertainty accounting method for this point.

<sup>69</sup>Using a 20% normally distributed error term and adding 20% on the average regional poverty rate when imputing for countries without data the poverty rates for 1990 and 2015 become 39.09 (SD 14.63) and 11.45 (SD 7.58) respectively, and the confidence level of fulfilling MDG1 is 79%.

<sup>70</sup>A procedure used by Hansen (2000) and by the World Bank in the article that gave birth to the DAD method as currently applied Ravallion et al. (2009), and by propagation also used in the latest update of the iPL using the DAD method Ferreira et al. (2015). See materials and methods for the details.

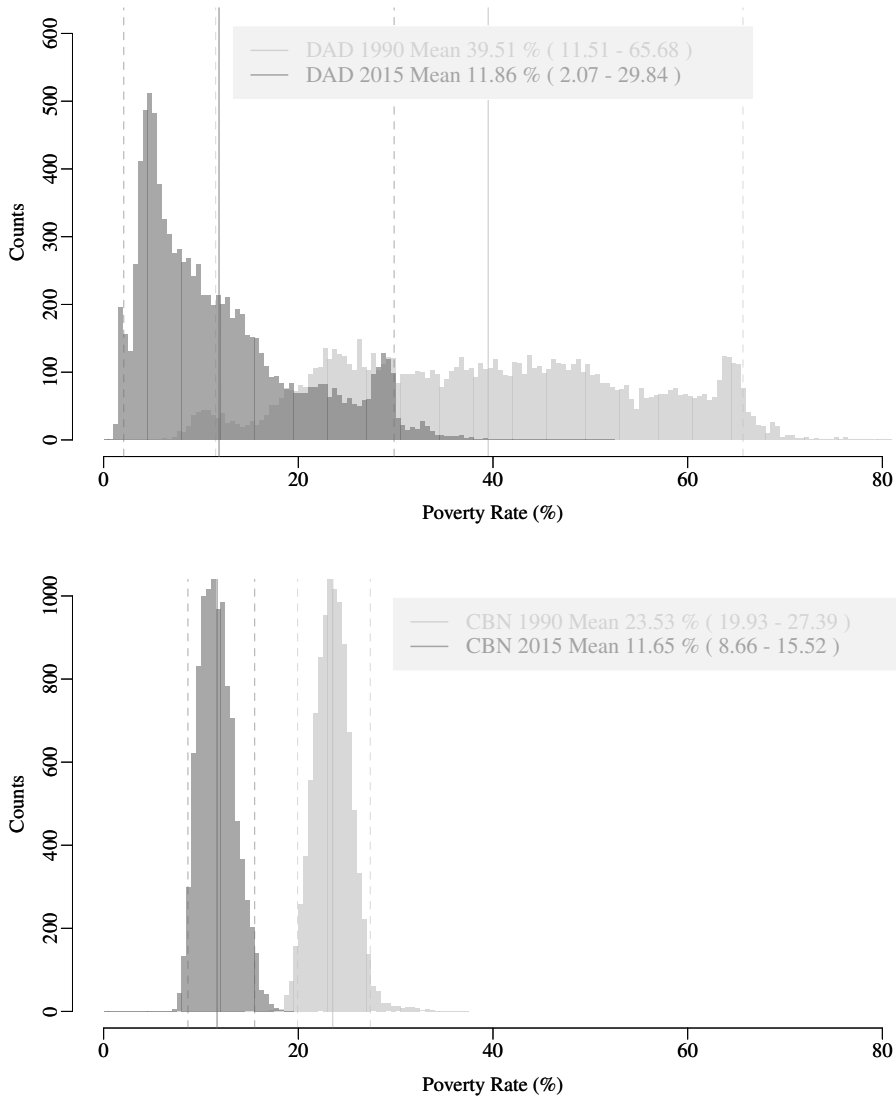


Figure 4.6: Histograms of Global Poverty Rates of most complete implementations. DAD implementation 4 in the upper sub-plot, and CBN implementation 5 in the lower sub-plot. Each distribution is composed of 10000 points. The values of the 95% confidence interval of each distribution is shown in parenthesis, and its average value precedes it.

31.17%. Finally, in implementation 7 we remove the consideration for the consistency check for the PPP draws that do not result in a consistent solution for the reference group.<sup>71</sup> This step drops the SD for iPL and poverty rates for both benchmark years further, and the confidence of achieving MDG1 rises to 90%. The identified poverty reduction rises to 40.34% at 95% confidence level, and it is the closest we obtained to the MDG1 target of 50% poverty rate reduction.

In most implementations the identified DAD poverty rates standard deviations demonstrate high relative values, typically more than 35% and very often as much as 50% or 60% and above (IDs 1-4, and for both benchmark years). This is mainly the result of three forces working in the same direction: (a) the uncertainty from taking an average to construct the iPL, (b) the underlying PPP standard deviations,<sup>72</sup> and (c) the frequent inconsistency of reference group formation of the DAD method. However, even without considering point (c) our results indicate that MDG1 was not fulfilled at a 95% confidence level (implementations 1, 2, 3 and 7)

Finally, table 4.4, shows global poverty estimates and probabilities of the success of an alternative MDG1 appropriately formulated for the CBN approach.<sup>73</sup> In all cases, the success of the goal of poverty reduction by 50% in the 1990-2015 period at 95% cannot be concluded. The mean values of the CBN based estimates appear rather steady among the various implementations, remaining around 23.5% for 1990 and 11.5% for 2015. In comparison to the DAD, the CBN approach shows considerably smaller relative standard deviations slightly short of 9% on average and 20% at maximum. Comparatively, this can be explained by the lack of uncertainty from averaging NPLs to produce an iPL, and no PPP uncertainty, since no PPP exchange rates are necessary in CBN. It is clear from these figures that the CBN approach delivers a more precise set of global poverty estimates in all cases investigated (see notes on table 4.4 for implementation details; the structure of the table is identical to that of table 4.3).<sup>74</sup> This point is made evident also from

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<sup>71</sup>Those draws are simply disregarded and a new draw takes place until 10000 consistent solutions are achieved; this also applied in implementations 1-3. See materials and methods for the details.

<sup>72</sup>Concerns with respect to the methodological appropriateness of the PPP standard deviations used here should find satisfactory response from the robustness check using half the original standard error values provided by Rao et al. (2015). This is done based on the complete scenario (ID 4 on table 4.3), and estimates an MDG1 confidence level of 85% and a poverty reduction at 95% confidence level of 27.41%.

<sup>73</sup>See materials and methods for the exact construction of the CBN poverty lines. Such MDG1 would specify the consumption basket underlying the desired welfare level of poverty we wish to see being reduced by half in the 1990-2015 period. As discussed above, for reasons of comparison with DAD, we construct here a consumption basket that gives similar average poverty rates for 2015 as the DAD method.

<sup>74</sup>The population coverage for DAD method is 88.6% and 82.6% for CBN in 1990, while for 2015 coverage rates are 88.3% and 81.7% respectively. Given the relative size of uncertainties the

the comparison of the lower sub-plot in figure 4.6, which depicts the most complete CBN implementation (ID 5), to the DAD sub-plot, and the clearly narrower breadth of the CBN global poverty estimates relative to those of the DAD method.

Table 4.4: CBN Global Poverty estimates

Implem. ID	Mean 1990	SD 1990	Mean 2015	SD 2015	MDG1 Conf. Level (%)	Pov. Reduc. (%)
1	23.58	0.93	11.49	0.71	38	45.7
2	23.58	0.93	11.49	0.72	38	45.6
3	23.56	1.1	11.52	0.92	40	43.5
4	23.57	1.23	11.62	1.22	44	40.5
5	23.53	1.97	11.65	1.8	46	34.4
6	23.48	2.5	11.78	2.29	48	29
PCN	43.15*	-	11.62*	-	-	-

\*: World Bank PovcalNet estimates from

<http://iresearch.worldbank.org/PovcalNet/povDuplicateWB.aspx>, last visited on January 4th, 2019.

Notes on implementation IDs: (1) MDER calculation uncertainty included, (2) previous specification and a normally distributed 10% error term is added when imputing for countries with missing data, (3) previous specification and assume a 5% error in the mean of the income or consumption distribution, (4) previous specification and the standard deviations shown on table 4.1 are used for the consumption share rates, (5) previous specification and a 21% relative standard deviation is added on the prices used, (6) previous specification, but a higher relative standard deviation for prices at 31.5% is used as a robustness check.

## 4.4. Discussion

### 4.4.1 On the link between MDG1 and DAD

Under a certain point of view the formulation of MDG1 may seem to warrant for a very different estimation approach than the one developed here. According to that view, MDG1 requires us to measure the share of population in the developing world strictly under a very specific dollar value in PPP terms; \$1.25 exactly. The question then becomes, should this iPL be treated as a given parameter or as a stochastic variable as we do here. We adopt here the point of view that there is nothing sacrosanct about 1.25\$, and that the real question of interest, at least to us, is whether, when estimating the global poverty rate with the DAD method—for which there is little evidence to support that this method is not the one implied

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approx. 6.3% difference in population coverage between the two methods should not be viewed as worrisome.

by MDG1—we can make a quantified statement about it being reduced by a factor of 2 between 1990 and 2015, or not. We treat the iPL as an estimated stochastic variable—as also the method developed in RCS implies—in order to address this question within the MC framework.

#### **4.4.2 Comparing the 1990 and 2015 global poverty distributions**

In estimating the confidence level of global poverty reduction between the estimates of global poverty for 1990 and 2015 one needs to take random samples from the common iPL distribution independently for the two years, and compare them to identify if MDG1 has obtained. We use this approach for our results in accordance with the stochastic nature of the quantities being compared. Our approach therefore implies that there exists a true, unknown value of the iPL, for which we don't know precisely how it evolves in time and therefore it needs to be estimated at each and every point in time effectively as a distribution due to the uncertainties involved in its estimation process. This subsection discusses tentative alternatives.

It is perceivable that the findings presented in table 4.3 may seem misleading because of the idea stating that there should be only one PPP draw underlying each poverty rates pair comparison between 1990 and 2015. This rationale could probably be explained by the frequency that the ICP project produces PPP rounds: about once every 6-10 years, and the subsequent repetition of the entire series of estimates by the World Bank following each new ICP round. Nevertheless, ICP rounds should have been yearly, but budgetary and other constrains—irrelevant to the point made here—simply do not allow for yearly ICP rounds. In this—more appropriate—case, a methodologically and data wise ideal 1990 round should be used for 1990 and likewise the 2015 ICP round for 2015. There is no reason why the PPP rates—and their standard deviation—should be fixed at each ICP round, and our random sampling approach also simulates this lack of PPP rates with yearly frequency as they ought to be delivered. This point suggesting multiple PPP-benchmarks is corroborated by the updating procedure followed by the Madisson project, (Bolt et al., 2018, p.11), and by the recommendations of (Aten and Heston, 2010, p.176) in averaging different PPP estimates between benchmark years.

Even more rigidly, some may find the approach of fully independent draws for the two benchmark years hard to agree with, as they might expect that even if one does not know the exact level of the iPL in 1990, whichever that level might be it must be exactly the same also for 2015 when the reduction rate between those years is estimated. If one accepts such a strict reading, such as the one discussed in the previous sub-section, then any error consideration regarding the rate of reduction would be meaningless, and the comparison between the two benchmark years would be as if error-less.



Although we consider that this entire notion of fully inter-yearly dependent iPLs builds on the idea that PPPs are error-less, we discuss here an alternative approach that can be used which avoids strict independence, and instead opts to produce critical values regarding how the iPLs from 1990 and 2015 are paired in the sampling procedure. For this purpose, we use the mean absolute difference (MAD) between the randomly selected iPLs for 1990 and 2015. This MAD is the condition that the 1990/2015 iPL pairs must satisfy in order to guarantee that the values of those lines are closely linked. The complete scenario (ID 4 in table 4.3) requires a 0.33 MAD value (in 2011 PPP dollars) so that it supports the success of MDG1 at 95% confidence level. The baseline scenario (ID 1 on the same table) requires an MAD value of 0.35 (see figure 4.7 for the full curves).

Now we need to find empirical evidence against which to compare these values. This will allow us to indicate if those critical MAD values are too restrictive or too loose. If they are too restrictive (loose) it will mean that the actual MAD should be higher (lower), rendering the MDG1 unsuccessful (successful) at 95% confidence level.

We took stock of all the poverty rates published by WB based on NPLs, and then inverted them using the PovcalNet data to get the implicit NLP value (this is the method applied by World Bank Poverty and Inequality Team researchers Jolliffe and Prydz (2016)). Figure 4.8 shows the results of this investigation. The NPLs we calculate this way are paired on a per country basis. The x axis indicates that NPLs at point t on x axis have at least t years of difference between them. Each line on the graph is produced by a different split of the data, depending on the maximum PPP dollar value allowed in the set as marked in the figure's legend.

The lower the maximum value allowed the lower the number of NPLs in the group. For the time span of 25 years that we are interested in, there are simply not enough data available. However, all the trajectories in the graph imply that we would get an MAD somewhere in the area between 0.35 and 0.4, close but above the critical MAD values. Therefore this supplementary approach does not seem to challenge our findings, but rather indicates a trajectory that would support them.

Comparing the critical MAD values with some reference values can also be addressed using the NPLs calculated here based on the cost of basic needs approach. Those poverty lines do express the same goal (nearly barebone subsistence with some frugal additional expenses), and their volatility with respect to their PPP dollar value is indicative of the consistency of the PPP assumption for the consumption needs of those living in conditions of extreme deprivation. The MAD for the CBN is 0.39 for the 25 years span of MDG1, which would make the 0.33 or 0.35 values appear rather restrictive.<sup>75</sup>

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<sup>75</sup>Do note that since the CBN NPLs adjust for changes in the underlying demographics of each country, (a small) part of this larger MAD should be attributed to this aspect of the CBN NPLs. The

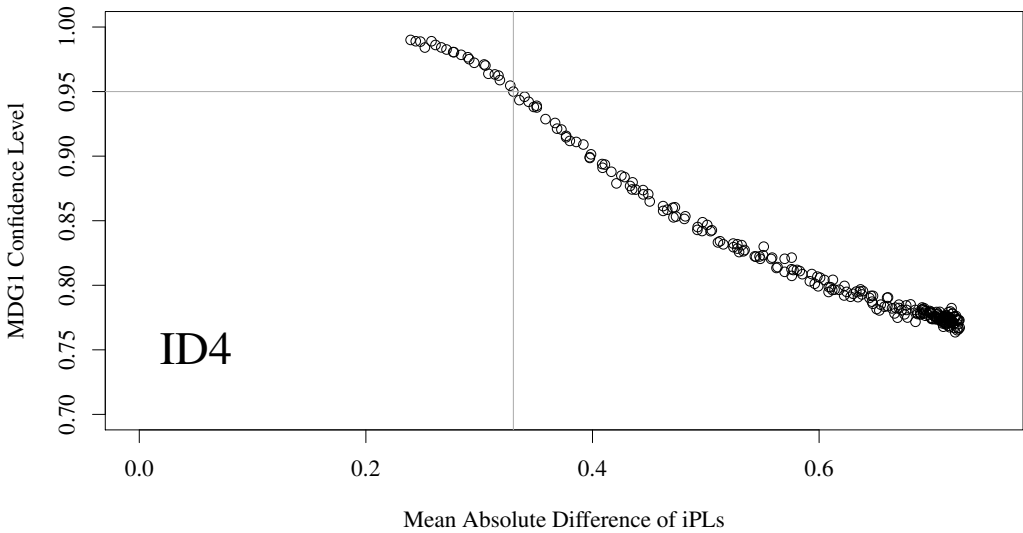
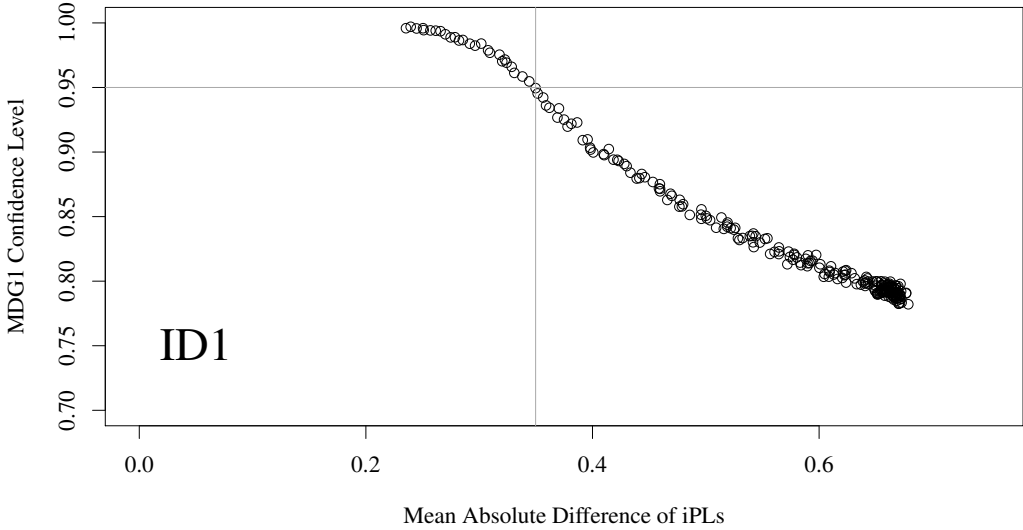


Figure 4.7: Critical MAD values for the baseline (ID1) and complete (ID4) scenarios. Vertical lines at critical values 0.35 (ID1) and 0.33 (ID4).

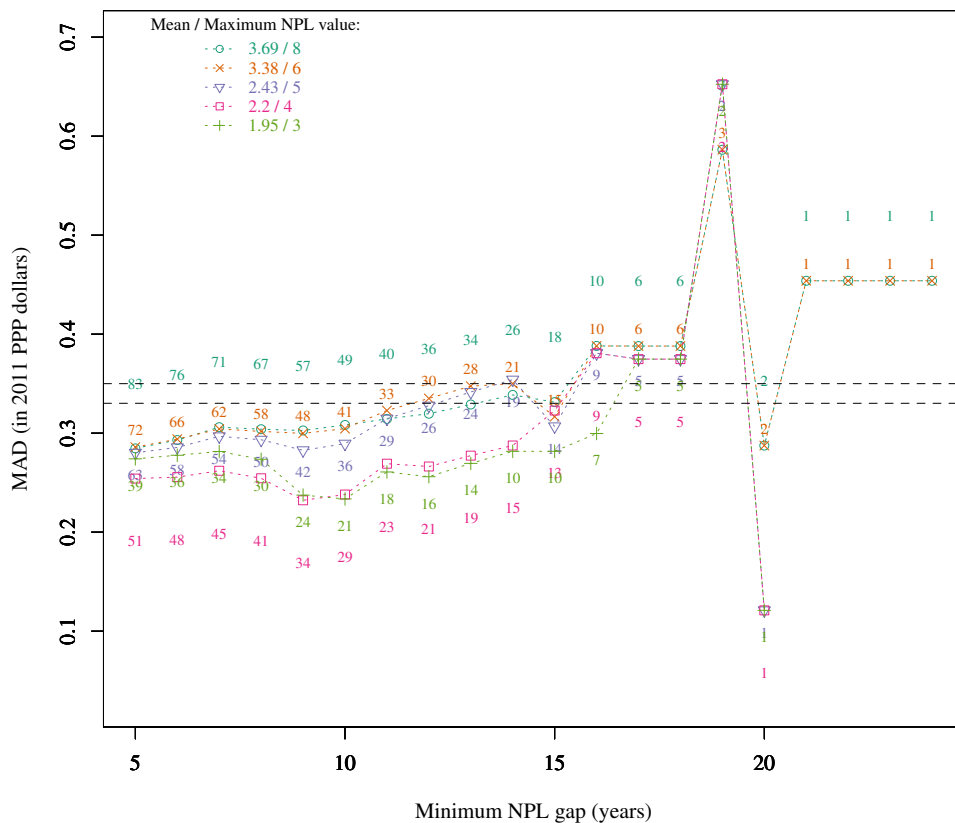


Figure 4.8: MAD evolution of estimated NPLs as a function of the minimum gap of years among same country NPLs. Numbers near the lines represent the number of observations  $N$  at each point. Horizontal dashed lines at critical values 0.35 (ID1) and 0.33 (ID4).

Regardless, since we don't have a set of actual official NPL values, but instead we estimate them indirectly, an alternative interpretation presents itself. Such an interpretation would state that the MAD as a function of years between NPLs (from the same country) is increasing in time because of differences in the underlying methodologies of the household surveys. But this should find satisfactory response in the fact that it is only the mean absolute difference that increases, while the mean difference remains very close to zero.

#### 4.4.3 Omitted error sources

As it can be seen from table 4.2 we are not treating all possible sources of non-sampling error identified by Atkinson (2016). Also, in some cases the treatment we operationalize is a crude and horizontal one, such as for HHS consumption (or income) measurement error, while in other cases we only provide treatment for one of the two methods that we compare.

The important question, however, is whether the items that are not treated threaten the validity of our results and conclusions. If in the future a reliable method to estimate the missing non-sampling uncertainties emerges—as the Commission on Global Poverty strongly advocates that it should—the total non-sampling uncertainty of global poverty estimates can be obtained by adding these uncertainties to the one we arrive at, in quadrature, assuming that the missing uncertainties are reasonably uncorrelated with the ones provided in this work. This will certainly increase the total uncertainty, so our results here can be seen as a lower bound to the unknown total uncertainty. In case there are missing effects that are strongly correlated, their uncertainty should be added linearly to the present one, hence the total would increase further. In order for the total uncertainty to shrink, one has to assume that some of the missing effects are not only as significant, in magnitude, as the ones included, but also strongly anti-correlated to the latter, and that on a global scale. In fact, in order to invalidate the main result of the paper, one needs spectacular decrease in the uncertainty estimates, since as shown in the results section, the uncertainty on the success of DAD poverty rates is rather large, and the confidence level where MDG1 obtains is within a considerable distance from the more typical value of 95%.

## 4.5. Conclusions

We have hereby shown that, as extensively advocated by the Commission on Global Poverty report, the uncertainties of the DAD global poverty estimates should be

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analysis found in figure 1 in Moatsos (2017a) indicates that the median of the between benchmark years change that should be attributed to the change in the underlying demographics is 5.6%.

accounted for as they are of considerable magnitude. Using the findings presented above, the number of people living in conditions of absolute poverty in the world's developing countries in 1990 stands between 504 and 2877 million people, while in 2015 the interval is between 130 and 1871 million.<sup>76</sup> We further show that MDG1 was achieved at a confidence level of less than 80%, considerably lower than the typical benchmark of 95%. Moreover, using the most complete error accounting scenario for the DAD method, we find that at 95% confidence level no reduction in global poverty is identified.<sup>77</sup> However, given the considerable poverty reduction identified by the CBN method in the same period, we form the opinion that the inability of DAD to identify any poverty reduction in the MDG1 period says more about the uncertainties of the method per se, than about the evolution of global poverty.

We acknowledge that perhaps at the level of implementing legislation towards poverty reduction, lower confidence levels could be quite acceptable. However, it is debatable how low the confidence level in testing MDG1 success should be, given the importance of how our world view may be influenced by receiving a positive or a negative message regarding the world's capability to succeed in halving global poverty within 25 years. Especially when this is framed as the first ranking global development goal. In any case, the discussion about which would be the desired or acceptable confidence level, has not taken place for the purpose of monitoring global poverty reduction goals. We believe that such dialogue is long overdue, also with respect to SDG1.1. Given the central role of poverty reduction—among others—in the development goals agenda, one could argue that not only each global poverty estimate should come with an uncertainty estimate, but also that long term goals like SDG1.1 should be stated with a concrete measure of success in terms of confidence levels.

The officially reported DAD point estimates show a remarkable 73% reduction of global absolute poverty between 1990 and 2015. This stands in stark contrast with our findings and in our view this shows that not only the comparison of point estimates of DAD results gives an overly optimistic picture of the fight against poverty, but also when the same method is used, and the underlying uncertainties are included, one is led to believe that no conclusive statement about poverty reduc-

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<sup>76</sup>Based on the 95% confidence level of poverty rates in the results from implementation 4 of table 4.3, and the population in developing countries for 1990 and 2015.

<sup>77</sup>Arguably, this might seem to many as a very disappointing—and perhaps even counterintuitive—result. Interestingly though, and perhaps for completely different reasons, public perception as captured by a Glocalities global survey, indicates that this is not counterintuitive to many, and as cited in Pogge (2017); "70% of respondents believe that global poverty has increased by a quarter or more since 1990, 18% believe it has stayed about the same, 12% believe it has declined by a quarter and only 1% believe it has been cut in half." [www.glocalities.com/news/poverty.html](http://www.glocalities.com/news/poverty.html) last accessed October 8, 2018.

tion can be drawn. Given that the critical step producing the bulk of the uncertainty for the DAD method comes from the averaging of NPLs, it appears that updating the DAD method, and substituting the averaging with another procedure, may produce confidence levels much higher than the 77% we have identified here. Alternatively, decomposing the NPLs in the Ferreira et al. (2015) dataset into absolute and relative components, as the theory behind Ravallion et al. (1991a) stipulates, may give more accurate estimation of the implied iPL even if an averaging method would still be used. This last point is corroborated by the closer dispersed NPLs that Allen (2017) estimates for the same reference group, using his “basic diet” setup.<sup>78</sup> We find our results to be in line with his suggestion to use such a CBN configuration as the basis for global poverty measurement.

Finally, we take that the above observations unequivocally suggest that—as extensively advocated by the Commission on Global Poverty report—a global CBN approach in line with the recommendation 15 of the report offers valuable and evidently more accurate and transparent—with respect to its encapsulating poverty definition—information in the progress of the fight against global poverty.

## 4.6. Appendix

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<sup>78</sup>Not all estimates for the countries in World Bank’s reference group are available in Allen (2017) article, but their standard deviations (communicated to us by personal correspondence) for a “basic diet” setup is 0.6 (with an average of \$1.92), compared to the 0.68 for the NPLs in the reference group of Ferreira et al. (2015). The difference on the full sample is small, with the bulk of deviation in Allen’s PLs coming from a single observation (Tajikistan) and is probably the result of highly unreliable data for this particular country. Once this country is excluded, the SD drops to 0.24 (average \$1.78), while doing the same with the NPLs used in Ferreira et al. (2015) gives an SD of 0.60, maintaining the bulk of its variance. Therefore in all likelihood, such a foundation could allow for a DAD version that would be numerically sharp enough for global poverty measurement. Please note that the “basic diet” calculations for the countries in the dollar-a-day reference group are preliminary and subject to change.

Table 4.5: **Elbow fitting original.** Numerical results for the elbow fitting of the Ravallion et al. (2009) data set for the first 30 countries. All monetary values in 2011 PPP dollars per month, except iPL that is given in per day values. (b) and (c) correspond to the criteria (b) and (c) described in the text; 1 corresponds to fulfilling the criterion and 0 for not.

	ISO3	Cons.	$C^*$	iPL	beta0	beta1	(b)	(c)	DAD
1	MWI	31.34		26.110					0.86
2	MLI	31.96	39.311	34.000	21.403	0.320	1	0	1.12
3	ETH	35.22	47.387	36.347	21.128	0.321	1	0	1.19
4	SLE	36.94	60.853	40.145	20.500	0.323	1	0	1.32
5	NER	39.34	56.657	38.786	20.495	0.323	1	0	1.28
6	UGA	40.01	56.994	38.740	20.313	0.323	1	0	1.27
7	GMB	40.88	60.812	39.623	19.895	0.324	1	0	1.30
8	RWA	41.33	56.858	38.441	20.014	0.324	1	0	1.26
9	GNB	45.12	60.576	39.277	19.575	0.325	1	0	1.29
10	TZA	45.26	52.797	37.269	20.180	0.324	1	0	1.23
11	TJK	45.49	61.433	39.229	19.187	0.326	1	0	1.29
12	MOZ	45.52	58.454	38.422	19.381	0.326	1	0	1.26
13	TCD	47.04	54.711	37.512	19.742	0.325	1	0	1.23
14	NPL	54.55	50.939	36.721	20.240	0.324	0	1	1.21
15	GHA	56.90	56.935	37.983	19.448	0.326	1	1	1.25
16	ZMB	60.40	57.336	38.089	19.420	0.326	0	1	1.25
17	NGA	61.49	55.062	37.695	19.821	0.325	0	1	1.24
18	BGD	64.34	52.722	37.348	20.297	0.323	0	1	1.23
19	BFA	68.54	48.587	36.765	21.155	0.321	0	1	1.21
20	COG	72.13	56.908	38.327	19.861	0.324	0	1	1.26
21	BEN	72.82	51.683	37.624	20.999	0.322	0	1	1.24
22	KHM	75.06	52.037	37.859	21.138	0.321	0	1	1.24
23	YEM	76.37	59.018	39.055	19.914	0.324	0	1	1.28
24	SEN	78.92	51.825	38.222	21.630	0.320	0	1	1.26
25	MNG	80.55	56.201	39.008	20.918	0.322	0	1	1.28
26	VNM	81.18	52.599	38.758	21.961	0.319	0	1	1.27
27	IND	84.24	46.794	38.338	23.578	0.315	0	1	1.26
28	PAK	98.31	47.353	38.778	23.875	0.315	0	1	1.27
29	MRT	99.63	53.449	39.791	22.838	0.317	0	1	1.31
30	KGZ	109.85	56.361	40.492	22.582	0.318	0	1	1.33

Table 4.6: **Elbow fitting amended.** Numerical results for the elbow fitting of the Ravallion et al. (2009) data set for the first 30 countries, with the slight modification of Bulgaria's (BGR) PPP rate (see text for details). All monetary values in 2011 PPP dollars per month, except iPL that is given in per day values. (b) and (c) correspond to the criteria (b) and (c) described in the text; 1 corresponds to fulfilling the criterion and 0 for not.

	ISO3	Cons.	$C^*$	iPL	beta0	beta1	(b)	(c)	DAD
1	MWI	31.34		26.110					0.86
2	MLI	31.96	39.283	34.000	21.416	0.320	1	0	1.12
3	ETH	35.22	47.360	36.347	21.141	0.321	1	0	1.19
4	SLE	36.94	60.830	40.145	20.514	0.323	1	0	1.32
5	NER	39.34	56.632	38.786	20.509	0.323	1	0	1.28
6	UGA	40.01	56.968	38.740	20.328	0.323	1	0	1.27
7	GMB	40.88	60.786	39.623	19.910	0.324	1	0	1.30
8	RWA	41.33	56.830	38.441	20.029	0.324	1	0	1.26
9	GNB	45.12	60.548	39.277	19.591	0.325	1	0	1.29
10	TZA	45.26	52.766	37.269	20.196	0.324	1	0	1.23
11	TJK	45.49	61.404	39.229	19.204	0.326	1	0	1.29
12	MOZ	45.52	58.422	38.422	19.398	0.326	1	0	1.26
13	TCD	47.04	54.676	37.512	19.759	0.325	1	0	1.23
14	NPL	54.55	50.901	36.721	20.258	0.323	0	1	1.21
15	GHA	56.90	56.899	37.983	19.466	0.325	0	1	1.25
16	ZMB	60.40	57.298	38.089	19.439	0.325	0	1	1.25
17	NGA	61.49	55.021	37.695	19.841	0.324	0	1	1.24
18	BGD	64.34	52.679	37.348	20.317	0.323	0	1	1.23
19	BFA	68.54	48.541	36.765	21.176	0.321	0	1	1.21
20	COG	72.13	56.863	38.327	19.883	0.324	0	1	1.26
21	BEN	72.82	51.634	37.624	21.021	0.322	0	1	1.24
22	KHM	75.06	51.986	37.859	21.161	0.321	0	1	1.24
23	YEM	76.37	58.967	39.055	19.938	0.324	0	1	1.28
24	SEN	78.92	51.769	38.222	21.654	0.320	0	1	1.26
25	MNG	80.55	56.144	39.008	20.944	0.322	0	1	1.28
26	VNM	81.18	52.538	38.758	21.988	0.319	0	1	1.27
27	IND	84.24	46.726	38.338	23.605	0.315	0	1	1.26
28	PAK	98.31	47.283	38.778	23.904	0.315	0	1	1.27
29	MRT	99.63	53.378	39.791	22.868	0.317	0	1	1.31
30	KGZ	109.85	56.288	40.492	22.613	0.318	0	1	1.33



## Chapter 5

# Global Income Distribution & Inequality since 1820

by Michail Moatsos, Joerg Baten, Peter Foldvari, Bas van Leeuwen and Jan Luiten van Zanden<sup>1,2</sup>

*“Everyone can enjoy a life of luxurious leisure  
if the machine-produced wealth is shared,  
or most people can end up miserably poor  
if the machine-owners successfully  
lobby against wealth redistribution.”  
Stephen Hawking<sup>3</sup>*

This chapter focuses on income inequality as measured by gross (i.e. pre-tax) household income across individuals within a country. It builds upon a number of large-scale initiatives to chart income inequality trends over time, supplementing them with data on wages and heights for the earlier period. Income inequality

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<sup>2</sup>The usual disclaimer applies. Moatsos et al. (2014).

<sup>3</sup>"Stephen Hawking Says We Should Really Be Scared Of Capitalism, Not Robots"

trends follow a U-shape in most Western European countries and the Western Offshoots. It declined between the end of the 19th century until about 1970, followed by a rise. In Eastern Europe, communism resulted in strong declines in income inequality, followed by a sharp increase after its disintegration in the 1980s. In other parts of the world (China in particular) income inequality is on the rise recently. The chapter also provides evidence on the global income distribution, i.e. assuming all people belong to the same community. This distribution was unimodal in the 19th, became increasingly bi-modal between 1910 and 1970 and suddenly reverted back into a unimodal distribution between 1980 and 2000.

## 5.1. Introduction

The importance of income inequality at the local, regional and global scale hardly needs to be stressed: the enormous increase of income inequality on a global scale is one of the most significant – and worrying – features of the development of the world economy in the past 200 years (Zanden van et al., 2013). Several international organisations and commentators have drawn attention to the increase in income inequality in a number of developed and emerging countries in the run-up to the recent global financial crisis. For these reasons, the subject has become one of the most discussed topics in the social sciences; in particular, the debate on the measurement and interpretation of recent trends in global inequality – is it still increasing? and why or why not? – has attracted considerable attention (Anand and Segal (2008); Bourguignon and Morrisson (2002); Deininger and Squire (1996); Milanovic (2002b, 2007); Jones (1997)).

Levels and trends in income inequality are very relevant for people's and societies' well-being. In a sense, the information that income inequality provides is additional and complementary to that referring to average personal income. Since an increase in GDP per capita, by itself, gives us information only about average income gains, income inequality provides more detailed insights about how much the benefits of economic growth in a society or region are spread. It tells us who is getting the benefits of economic growth, and in what proportions. Besides this connection with well-being, an extensive literature investigates the impact of income inequality on a range of social outcomes, such as trust, crime, social mobility, health and educational achievement (Wilkinson and Pickett, 2007).

In what follows, we address and document the long-run trends in income inequality. First we present a new long-run dataset on income inequality (Zanden van et al., 2013) that has the benefit of internal consistency, but also makes it possible to describe, for the first time, historical developments in income inequality on a global scale spanning about two hundred years. Second, we use this dataset to describe historical developments in income inequality both within and between countries.

## 5.2. Description of the concepts used

The analysis presented in this chapter refers to the distribution of gross (i.e. pre-tax) household income across individuals, with inequality in this distribution described by the Gini coefficient. Both choices are not uncontroversial.

First, because alternative measures of household economic resources (e.g. post-tax income, consumption, including or excluding a range of more detailed components such as imputed rents or capital gains) and alternative units of analysis (e.g. households, or consumption units based on different “equivalence scales”) are typically used to examine income inequality. We selected gross household income as the measure in focus due to the availability of historical data: the further back we go in time, the more data is available in gross (pre-tax) household income terms, rather than in other forms. As using different definitions can lead to different conclusions about trends in income inequality, the data we assembled in this dataset are either based on gross household income or have been converted to a gross household income basis using various adjustments (see below for details).

Second, because other inequality measures also exist, such as the Theil index, which do not always display similar levels or trends when applied to the same distribution. However, even though many other measures have interesting properties (for example, the Theil coefficient is additive), the use of the Gini coefficient is widespread in the literature on income inequality. In addition, the Gini coefficient is used in the data sources that we heavily rely upon as a primal source of income inequality data. Hence, in this chapter we will focus on this measure.

As it is explicitly developed as a measure of income inequality, the Gini coefficient has some particular properties that make it appealing. One is that it has a direct relationship with the so-called Lorenz curve, which is obtained by plotting the cumulative percentage of income held by the cumulative percentage of the reference population. The Gini is proportional to the area between the line indicating perfect equality and the Lorenz curve, and hence is increasing with the degree of inequality. So a Gini of 0 indicates perfect equality, while a Gini of 1 indicates perfect inequality.<sup>4</sup> Another definition of the Gini coefficient is in terms of income differences between every pair of individuals in a population (Sen, 1973, 1976). An important property of the Gini coefficient is that any income transfer from the rich to the poor leads to a decline in the measure (i.e. the Gini coefficient moves in the “right” direction). However, as mentioned above, the Gini coefficient also has

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<sup>4</sup>So a Gini coefficient equal to zero implies perfect absolute equality – i.e. all individuals have the same income – and a Gini equal to one implies absolute inequality – i.e. one individual has all the income while the rest have none. The actual impossibility of having a Gini equal to one fits well with the idea of an inequality-possibility frontier, which takes into account the subsistence income as a frontier for minimum income for survival, and of maximum possible inequality if one individual were to receive all the remaining income (Milanovic, Lindert and Williamson, 2007).

some less desirable properties, one of which is that the same Gini can be derived from very different income distributions. For example, two very different situations, one where the middle and upper classes have a much higher income than the lower class, and a second where the upper class is extremely rich compared to the other two strata, could in principle lead to the same Gini coefficient. More generally, the Gini coefficient is most sensitive to the part of the income distribution around the median (Buhmann et al., 1988).

Gini coefficients can be calculated on the basis of different income and population concepts. For example, they can refer to households or individuals, and be based on either gross (i.e. pre-tax) or net income, or on either income or consumption, or they can refer to either urban centres or the whole country. More generally, estimates of the Gini coefficient obviously depend on the data produced by statistical offices, as they require consistency over time in the concepts used and the underlying data sources (e.g. household surveys or administrative tax records), in measurement conventions, and other methodological choices. These difficulties are obviously compounded when trying to obtain historical estimates reaching back to 1820.

Beyond providing an historical perspective on income inequality in individual countries, this chapter has an additional goal: to describe changes in the global distribution of household income, i.e. the distribution that one would observe when treating all people in the world as if they were living in a single country. This implies additional challenges relative to that of reconstructing historical series of within-country income inequality, as it requires combining information from both micro-sources (e.g. tax records or surveys) and macro-sources (e.g. national accounts). This is a challenge, and requires additional assumptions, e.g. that levels and trends in the reference income variable from micro- and macro-sources are the same, an assumption that in reality may not always hold true. In the database used in this chapter, the assumption made is that cross-country differences in average household income can be proxied by differences in GDP per capita.

### 5.3. Historical sources

There is no single repository of Gini coefficients that contains estimates for every country and for every year. Hence, we relied on a variety of different sources to construct our dataset. For the post-1960 period most of our data came from the World Income Inequality Database (UNU-WIDER, 2008), a large compilation of country estimates coming from a variety of individual sources. For earlier periods, data were taken from a range of historical sources<sup>5</sup> and from studies on the top-

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<sup>5</sup>Studies are available for Australia (1921-2003, Atkinson and Leigh (2007)); Canada (1920-2000, Saez and Veall (2005)); France (1905-1998, Piketty (2007)); Germany (1925-1998, Dell

income share that have recently become more widely available (Atkinson et al., 2011). A good overview of most of the historical work on income inequality can be found in (Milanovic et al., 2007), and at the Global Income and Prices website at UC Davis.<sup>6</sup> Additional recent work has been done, for example, by Bértola et al. (2009) for parts of South America, Bértola et al. (2009) for Italy, Bértola et al. (2009) for the Soviet Union, and Soltow and van Zanden (1998a) for the Netherlands.

As stressed by François and Rojas-Romagosa (2005), the Gini values that are available from the World Income Database refer to various concepts and data sources: both levels and the trends pertaining to particular series can be very different. They distinguish three main concepts, due to the differences in trends: gross household income, net household income and expenditure data.

In the construction of the dataset used in this chapter, we followed the methodology suggested by François and Rojas-Romagosa (2005), and converted all available estimates of Gini coefficients into a gross household income basis. To that end, we tested (across a large sample of countries) the hypothesis that trends in Gini coefficients for gross and net household income were similar to those for household income and consumption. These tests suggest that this hypothesis holds true in all countries, with the exception of a relatively short period after the Second World War. Beyond this, average consumption may evolve differently from household income through borrowing and lending, and average expenditures are not a linear function of income since wealthy people tend to save more. Changes in all these parameters probably account for diverging trends in various types of Ginis observed in the after-war period. In that sense, the post-Second World War period is special, since many countries expanded their system of income taxation and made it more progressive. After 1980, trends between gross and net household income and expenditure are again quite similar, although this may not hold in specific countries and sub-periods.<sup>7</sup> Based on this empirical observation, we converted post-Second World War estimates of the Gini coefficient into a gross household income basis, by using regression techniques (the details are described in Zanden van et al. (2013)).

While using the World Income Database as a reference source, a range of other

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(2007)); India (1922- 1999, Saez and Veall (2005)); Indonesia (1920-2004, Leigh and der Eng (2010)); Ireland (1922-2000, Nolan (2007)); Japan (1886-2002, Moriguchi and Saez (2006)); Korea (1998, Cheong (2001)); Netherlands (1914-1999, Salverda and Atkinson (2007)); New Zealand (1921-2002, Atkinson and Leigh (2005)); Spain (1981-2002, Alvaredo and Saez (2009)); Sweden (1903-2004, Roine and Waldenström (2006)); Switzerland (1933-1996, Dell et al. (2007)); the United Kingdom (1908-2000, Atkinson (2007)); and the United States (1913-2004, Piketty and Saez (2003)).

<sup>6</sup>Global Price and Income History Group.

<sup>7</sup>For example, income inequality increased significantly in the United States since the 1980s, while consumption inequality was rather stable.

sources, including CEDLAS (2013)<sup>8</sup> and Milanovic (2012), have been used to extend this information back in time. The first type of information used is related to top-income share estimates, and in particular to the historical development of the share of the richest 1% or 5% in total income, which was pioneered by the work of Piketty and Atkinson.<sup>9</sup> These data, which basically refer to a single point on the Lorenz curve, can be converted into Gini coefficients using the assumption of log-normality in the underlying (and non-observed) income distribution. In other words, by assuming that the income distribution is log-normal, we can compute the Gini coefficient of a log-normal distribution that has a given income share for people at the very top. Like most of the assumptions made in historical analysis, the assumption of log-normality is not a perfect one, and there is room for error, particularly at the extremes of the income distribution. An alternative assumption that has been previously proposed in the literature is that household income follows a Pareto distribution. However, Soltow and van Zanden (1998b) has demonstrated that when the entire income distribution is considered, the hypothesis of a log-normal distribution is preferable.

For the period before the Second World War, there are only a few direct estimates of income inequality, and these are available only for a small number of countries.<sup>10</sup> For other countries in this period, we relied on a method inspired by the “extraction rate” concept Milanovic et al. (2007) to derive additional estimates. According to this method, changes in the Gini coefficient are linked to the development of the Williamson index, i.e. the ratio between the average family income (measured by GDP per capita) and the real wage of unskilled labour. When this ratio goes up, income inequality may also be expected to rise, and vice versa. The link has been tested empirically and used to extrapolate and interpolate Gini coefficients (details are supplied in Zanden van et al. (2013)). The sources used for the real wage of unskilled labour were Williamson (1999, 2000b,a), Mitchell (1998c,a,b), Allen (2001), Mironov (2004) and Allen et al. (2010), while estimates of the average family income were based on estimates of GDP per capita from Maddison (2003).<sup>11</sup>

Another source of information on income inequality in the 19th century comes from a method based on evidence of the footprint of income inequality on the hu-

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<sup>8</sup>Although SEDLAS sources in All The Ginis dataset are treated as “gross”, the data exclude wage taxes and include direct taxes. This may introduce some additional bias.

<sup>9</sup>The data available on income shares of the top 1% and top 5% can be found for a collection of countries at “The World Top Incomes Database” created by Facundo Alvaredo, Tony Atkinson, Thomas Piketty and Emmanuel Saez. We make use of these data, but we do not present them separately.

<sup>10</sup>For China from Brandt and Sands (1992); for Japan, several estimates by Soltow and van Zanden (1998a); for Indonesia, Leeuwen van and Földvári (2012).

<sup>11</sup>Both series are also used in (Zanden van et al., 2014, Chapters 3 & 4).

man body. Baten (1999, 2000), Baten (2000), Baten (2000), Baten (2000) and Baten (2000) have argued that the variance in height across individuals within a country (as measured by the coefficient of variation) can be used as a proxy for income distribution. As the studies included here use large samples, individual genetic differences average out. As higher-income people have access to better nutrition and shelter and suffer less from disease, they also tend to be taller, while the opposite applies to the lower-income strata. This fact can be used to link the variation in height of a certain cohort and the income distribution during the decade of their birth.<sup>12</sup> Historical data on height are available from hundreds of previously published articles, as summarized in (Zanden van et al., 2014, Chapter 7), and provided the basis for income inequality estimates for around one-third of our sample. Naturally, we excluded studies that referred to very small samples of height measurements, or to a special group within a given country. We were also cautious to avoid the distortion of our estimates by factors such as mixed-aged samples, military truncation, gender, prison or other sample selectivity issues.<sup>13</sup> Finally, for cases where these methodological approaches to the estimation of income inequality could not be applied, some of the remaining missing data on income inequality were estimated using multiple imputation methods. Besides the direct and indirect sources for income inequality information, estimates of average household income per capita are also necessary for our analysis of global inequality. As mentioned above, the proxy that we used for this was GDP per capita expressed in 1990 international dollars (the same series that is used in (Zanden van et al., 2014, Chapters 3)).

Table 5.1 gives an overview of the various sources used in this chapter by type of method used. Out of the 869 estimates used here, the WIID database supplied 43% of the data-points, various historical studies provided another 8%, changes in the Williamson index (the GDP/wage ratio) made it possible to estimate 6% of all estimates, and height data helped to make 33% of the country estimates. When both height data and GDP/wage ratio were available, Gini coefficients were estimated as the unweighted average of the two (8%).

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<sup>12</sup>The decade of birth is used, because the strongest environmental influence on the body growth process takes place after birth during the first three to five years.

<sup>13</sup>This measure could be affected by survivor bias, since measures of inequality in height refer only to survivors. However, this is consistent with other measures of inequality, as the income earners who are the base for Gini coefficients of household income only refer to people who survived to the age of earning an income. For further discussion, see Moradi and Baten (2005).

Table 5.1: Estimates of income inequality by source and year, 1820-2000. Number of countries.

Year	All	WIID	'New' ginis	GDP/wage ratio	Heights	Both 4&5 (50/50)
1820	39	0	6	6	18	6
1850	40	0	1	8	20	8
1870	54	0	11	5	27	11
1890	60	0	8	5	34	13
1910	71	1	10	7	43	10
1929	74	2	15	9	39	9
1950	81	13	10	8	41	9
1960	88	54	4	2	27	1
1970	94	60	2	2	29	1
1980	83	71	0	0	12	0
1990	99	98	1	0	0	0
2000	86	71	1	0	0	0
Total	869	370	69	52	290	68

## 5.4. Data quality

Table 5.2 presents our assessment of the quality of the data used. Most data concerning income inequality in the 19th century are based on indirect sources and subject to large margins of error, and hence are classified as “estimates”. Only recently does the quality improve a lot, reaching level one for many world regions in the most recent period. Income inequality at the regional level also requires the aggregation of income levels of individual countries, which greatly increases the problems involved.

Providing a historical perspective on income inequality at the global level is an even more demanding task. Although the United Nations (UNU-WIDER) now provides extensive data on within-country income inequality, they do not cover all countries for all years, and they are not necessarily from comparable sources Milanovic (2006). This data source provides inequality data gathered from various national sources and methodologies that vary across countries, and across periods for a given country.<sup>14</sup> This implies that both cross-country and inter-temporal comparability are an issue. Alternative sources, such as the estimates compiled by the OECD Income Distribution Database, are based on consistent definitions (e.g. in terms of the components included in the basic income concept) and treatments (e.g. in terms of treatment of negative income, or choice of equivalent scales), and are

<sup>14</sup>Beyond various between-country differences, there are a number of concerns embedded in the survey's methodology per se, particularly the under-representation or under-reporting of the poorer and richer groups of the population within a country.



Table 5.2: Quality of data on income inequality by region and benchmark year, 1820-2000.

Year	WE	EE	WO	LA	SSA	MENA	EA	SSEA	WORLD
1820	4	4	3	4	4	-	4	4	4
1850	4	4	3	4	4	4	4	4	4
1870	4	4	3	4	4	4	4	4	4
1890	4	4	3	4	4	4	4	4	4
1910	3	3	3	3	4	3	3	3	3
1929	3	3	3	3	4	3	3	3	3
1950	2/3	3	2/3	3	3	3	3	3	3
1960	2	2	2	2	2	2	2	2	3
1970	1	2	1	2	2	2	2	2	3
1980	1	2	1	2	2	2	2	2	3
1990	1	1	1	1	1	1	1	1	3
2000	1	1	1	1	1	1	1	1	3

Note: 1. High quality; 2. Moderate quality; 3. Low quality; and 4. Estimates. See the section on "Data Quality" in (Zanden van et al., 2014, Chapters 1) for a description of the quality criteria.

adjusted for breaks in statistical methodology. However, they are not used in this chapter, first, because the estimates are limited to OECD countries and, second, because the Gini coefficients available from the OECD refer to disposable income (i.e. net of taxes) and market income (i.e. net of taxes and public transfers), rather than to the gross income concept used in this chapter. As a result, the estimates shown here for individual countries since the 1970s and 1980s may differ significantly from those reported by the OECD in its own reports on the subject (e.g. Japan). The various methods we used to provide estimates for the missing values of our income inequality series, although quite elaborate, are also imperfect. A more straightforward approach to constructing a similar long-run dataset on income inequality is found in Bourguignon and Morrisson (2002). One feature of the methodology they applied for estimating income inequality values before 1950 was the assumption that within-country income inequality remained stable over time. Also, for large parts of the world, estimates from the post-1914 or post-1945 period were used to extrapolate the country-data available for the various time periods back to the 19th century. Despite these differences in methodology, the findings reported by Bourguignon and Morrisson are remarkably similar to those shown here.

## 5.5. Main highlights of trends in income inequality

In this section we highlight two main sets of results: the development of within-country income inequality and the evolution of global income inequality.

### **5.5.1 Within-country trends in inequality**

We begin by describing the long-run trends in income inequality in individual countries. A selection of the countries with data available for the long-run period from 1820 until 2000 is shown in Table 5.3. Values of the Gini coefficient on income inequality in 1820 ranged from the modest values of 33 for India, 35 for Poland and 38 for Spain, all the way up to 59 for the United Kingdom and France, 58 for Egypt and Turkey, and 57 for the United States. China (45), Canada (45), Germany (51), Japan (51) and Brazil (47) were among the countries in the middle ground. By 1850, all the countries shown in Table 5.3 experienced a decline in income inequality, followed by a renewed increase in the period up to 1870. However, the ups and downs of the 19th century are probably less informative than the broad trends.

Table 5.3: Income inequality in selected countries, 1820-2000, Gini coefficient normalized to 0-100 scale; RUS 1930-1980 refers to the Soviet Union.

	Western Europe (WE)					Eastern Eur. (EE)	Western Offsh. (WO)	Latin Amer.& Carib. (LAC)	Mid. E. & N. Afr. (MENA)	Sub-Saharan Africa (SSA)	East Asia (EA)	S. & S.E. Asia (SSEA)													
Year	GBR	NLD	FRA	DEU	ITA	ESP	SWE	POL	RUS	AUS	CAN	USA	MEX	BRA	ARG	EGY	TUR	KEN	NGA	ZAF	CHN	JPN	IND	IDN	THA
1820	[59]	[56]	[59]	[51]	[54]	[38]	[55]	[35]	[58]		[45]	[57]	[40]	[47]	[47]	[58]	[58]		[55]		[45]	[53]	[33]	[52]	[47]
1850	[43]	[48]	[54]	[40]	[51]	[32]	[46]	[36]	[54]	[41]	[27]	[44]	[32]	[37]	[34]	[63]	[37]				[33]	[46]	[39]	[42]	[42]
1850	[43]	[48]	[54]	[40]	[51]	[32]	[46]	[36]	[54]	[41]	[27]	[44]	[32]	[37]	[34]	[63]	[37]				[33]	[46]	[39]	[42]	[42]
1850	[43]	[48]	[54]	[40]	[51]	[32]	[46]	[36]	[54]	[41]	[27]	[44]	[32]	[37]	[34]	[63]	[37]				[33]	[46]	[39]	[42]	[42]
1910	42	47	55	44	49	35	57	28	40	41	41	51	51	38	51	42		[49]		[45]	39	52	31	42	42
1930	43	42	62	46	51	36	51	26	43	36	42	54	55	60	45	46	54	[55]		[59]	44	52	31	50	47
1950	30	36	58	47	43	35	40	23	36	38	36	39	52	49	41	39	49	56		52	32	36	35	54	39
1960	29	43	52	39	44	28	40	26	28	35	35	38	53	55	42	43	55	68	51	69	31	38	37	40	43
1970	29	36	45	40	39	35	37	29	23	32	34	36	56	58	35	43	52	50	35	67	28	35	40	44	44
1980	34	30	35	38	39	41	29	30	25	39	34	37	51	57	42	50	50	57	35	67	30	37	31	40	46
1990	39	32	37	49	33	34	31	31	26	42	32	40	48	59	43	54	44	49	44	63	34	36	40	39	50
2000	40	32	37	51	37	33	35	35	40		41	44	47	61	47	54	46	51	51	55	44	33	47	50	47

In the 20th century, the trends are more pronounced. In the period between the two world wars, income inequality in most countries in Western and Eastern Europe as well as in the Western Offshoot countries rose and then dropped again, considerably so after the Second World War. Egypt, China, South Africa, Brazil, Thailand and Mexico also follow this pattern closely. A notable departure from the pattern is Sweden, which experienced a decline in income inequality from 1890 until 1980. Among the Eastern European countries, Poland also defied this trend by recording a rather slow declining level of inequality throughout the late 19th century and first half of the 20th century. India also joined the group of outliers by maintaining a very low level of slightly increasing income inequality until around the Second World War. Finally, Kenya followed the trend in the first half of the 20th century, by experiencing an increasing income inequality, with a more rapid increase in the second half of the 20th century.

In the 1950s, most countries in Latin America, Asia and Africa also experienced increased income inequality, but to varying degrees. China seems to be the sole exception to this pattern, with a small decrease in income inequality from an already low level. In Europe and the Western Offshoots, the situation is more diversified, as income inequality declined in most countries but increased in others. Income inequality declined in Canada and the United States, and even more so in France, Germany, the former USSR, Spain and Australia. Conversely, income inequality increased in the Netherlands, Italy, Poland and, to a lesser degree, Sweden. The United Kingdom stands out in this period with a rather stable level of income inequality. In the 1960s, most countries experienced rather stable income inequality, although this declined in France and Sweden and increased sharply in Kenya and South Africa.

France is notable for a continuous decline in income inequality in the period from the interwar years until 1980. South Africa, Brazil and Mexico kept a high level in the 1970s, but inequality dropped sharply in Mexico, from a coefficient of 59 in 1970 to 47 by 1980. The decline was smaller in the case of Brazil, but still substantial. In South Africa, the decline in income inequality was mostly recorded during the 1990s. Starting from the 1980s, most countries experienced a rise in their inequality levels, although, based on our series, Japan maintained low inequality levels from the 1950s onwards. In the group of countries with rising inequality in the period since the 1980s, one of the most striking increases was in China, whose Gini coefficient rose by about half between 1980 and 2000.

The country with the highest income inequality over the entire period is South Africa, with a peak of 70 in the 1970s. Among the other countries, only Kenya in 1960 came close to that level, with a Gini coefficient of 68. For a long period from the beginning of the 20th century up until the 1960s, Poland achieved the lowest income inequality, with values of around 25. In the period as a whole, Spain

and Thailand had the most stable level of inequality, with values staying within a relatively small range. In contrast, the former Soviet Union experienced the largest changes in inequality, followed by South Africa and Sweden.

It is hard not to notice the sharp increase in income inequality experienced by the vast majority of countries from the 1980s. There are very few exceptions to this, with Japan being the most prominent one (i.e. a decline starting from a rather low level of income inequality). Another exception is South Africa, which started-off from a staggering Gini coefficient of 70 in 1970.

### 5.5.2 Trends in global inequality

Looking beyond trends in individual countries and regions, we obtain a global perspective by considering income inequality as if the world were one country. This is shown in the second column of Table 5.4 (the World Gini). Although global income inequality rises throughout the period, the third column (within-country inequality) clearly shows the “egalitarian revolution” in the mid-20th century, which translated into significant declines in this measure. However, this trend reversed strongly in the last decade, as within-country inequality levels returned to the values recorded in 1820. Overall, the increase in global inequality experienced from 1820 to 2000 was largely caused by an increase in between-country inequality (fourth column) rather than within-country inequality (third column). The exceptions to this pattern are the years leading to 2000, when the increase in within-country inequality just offset the decrease in between-country income inequality. Throughout the period as a whole from 1820 to 2000, global interpersonal income inequality increased by 30% (column 2), while between-country inequality increased from a very low level of 16 in 1820 to 56 by 1970. However, over the last 50 years, between-country inequality has remained broadly stable, dropping only in the last two decades of the 20th century, the second decline in the dataset since 1820.

Figure 5.1 presents the same information about the evolution of global inequality in a different way. Changes in the shape of this distribution in different periods reflect the combined effects of the increase in average income levels in individual countries, the changes in its distribution within countries, and the growth of countries’ population (all income levels are expressed in 1990 Geary–Khamis dollars). What is particularly striking is the change in the shape of the income distribution through time (for similar analyses of the more recent period, see Milanovic (2002b), and Sala-i Martin (2006)). Between 1820 and 1950, the world income distribution is unimodal and basically log-normal, although, looking at the 1950 distribution, a thickening of its right “wing” can already be noticed. Over the next few decades, a different distribution starts to emerge, with two separate peaks; while this pattern is already distinguishable in 1950, it becomes more pronounced

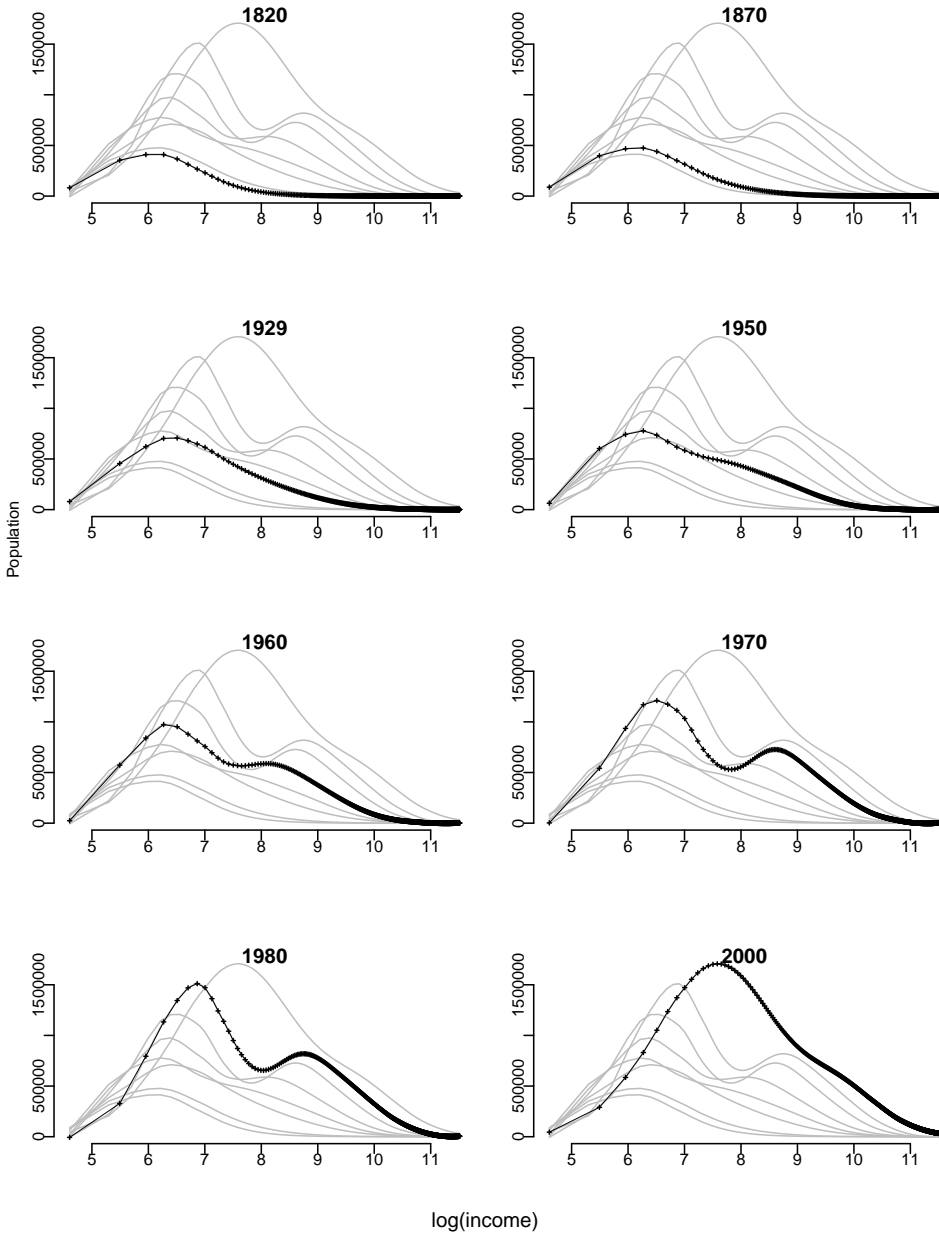


Figure 5.1: Global income distributions in selected years, 1820-2000. Thousands of people at given level of income in US dollars at 1990 PPP.

Table 5.4: Gini coefficients of within-country and between-country inequality, 1820-2000.

Year	World Gini	Within country inequality	Between country inequality
1820	49	45	16
1850	46	38	23
1870	55	45	32
1890	52	36	38
1910	58	40	44
1929	63	44	49
1950	65	38	55
1960	64	38	54
1970	65	37	56
1980	65	36	56
1990	66	39	56
2000	66	45	54

in the 1960s, 1970s and 1980s, when a big gap between the rich and poor “peaks” appears. However, in the 1990s the two peaks begin to get closer, and by 2000 the distribution has become unimodal again.

One might argue that the switch from a unimodal to a bimodal distribution in the 1960s was caused by the long wave of de-globalization that set in after 1914, i.e. a decline in external trade caused by two world wars, a depression and a bipolar world system. This, however, is a topic for further research – here we can observe only that this change from a unimodal world distribution towards a bimodal one was accompanied by the decline of within-country inequality: the “egalitarian revolution” of the 20th century seems to have been a phenomenon linked to the development of strong nation states, with more freedom to steer domestic policies in the de-globalized world of 1914-1960. However, almost simultaneously, these processes also gave rise to a bimodal income distribution globally. After 1980, globalization contributed to higher income inequality within countries, while at the same time leading to a decline of income inequality between countries, again in a closely interrelated process.

When looking more closely at the different world regions (Table 5.5), Latin America and the Caribbean is one of the regions with the highest average within-country inequality for the 20th century, as many would expect. The levels of its Gini coefficients are matched by those recorded in Sub-Saharan Africa from 1950 onwards. Furthermore, there seems to be one major reversal: in the 19th century, both Asia and Latin America and the Caribbean showed the lowest levels of inequality; this has completely changed by the end of the 20th century, which clearly

Table 5.5: Regional averages of income inequality, 1820-2000 Gini coefficients, unweighted averages.

Year	WE	EE	WO	LAC.	EA	SSEA	MENA	SSA	World
1820	54	51	56	45	45	35		53	45
1850	45	49	42	37	34	38	46	46	38
1870	50	48	51	48	41	42	52	50	45
1890	41	36	45	41	32	34	35	36	36
1910	46	39	50	45	40	35	40	42	40
1929	48	40	52	55	44	36	48	48	44
1950	42	35	39	47	33	39	43	43	38
1960	40	30	37	54	32	39	49	53	38
1970	38	26	36	53	29	40	47	49	37
1980	36	27	37	52	31	35	47	46	36
1990	38	27	39	52	34	41	46	47	39
2000	40	36	44	54	43	48	49	49	45

suggests that economic growth has led to a widening of between-country inequality in both regions. The decline in income inequality is also very strong in Eastern Europe and the former Soviet Union during the period from 1950-1990. After the dissolution of the Soviet Union and the fall of the “iron curtain”, this trend reversed and in the last two decades inequality has increased dramatically. Regional inequality in Western Europe and the Western Offshoots showed a major decrease in the period until 1980. Western Europe started off from a Gini of 55 in 1820 and went down to a more modest Gini of 37 in 1980. Since the 1980s, a small increase in the Gini coefficient has been observed. In the Western Offshoots, the pattern is very similar, but the rise in recent decades is much stronger. In Asia, the story is quite the opposite, at least in its beginning: starting from a low value in 1820 of 45 and 35, for East Asia and South and Southeast Asia respectively, both regions experienced a strong increase, which is most prominent in the 1960s for East Asia and in the 1980s for South and Southeast Asia. This rising trend also extended to the last three decades as well.

### 5.5.3 Correlation with GDP per capita

Figure 5.2 shows the correlation of GDP per capita with income inequality for all countries, with data being divided into three main periods and shown in a semi-logarithmic form. The first panel in the figure refers to the period before the 1930s, the next panel to the period from 1950 to 1970, and the last panel to the period from the 1980s onwards. In the first period, a negative correlation between GDP per capita and income inequality appears for countries with the lowest annual incomes; that correlation turns positive among countries with incomes from USD 800 up to



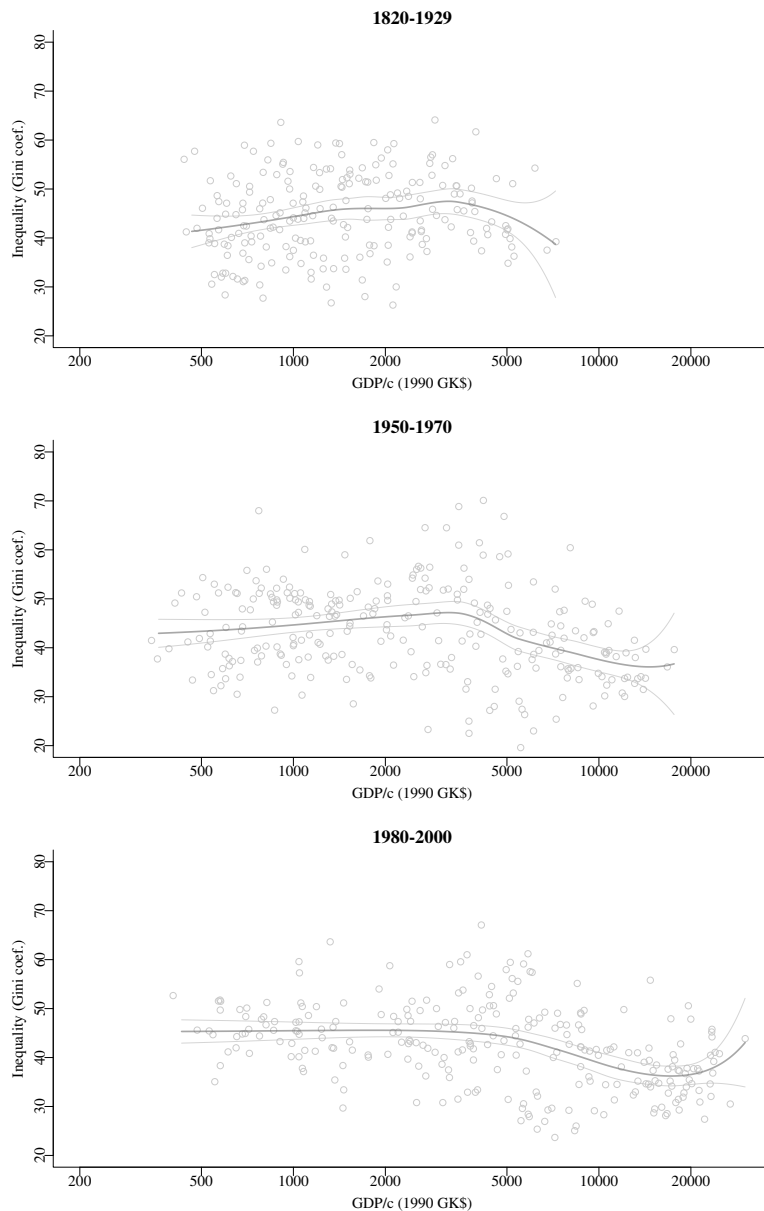


Figure 5.2: Correlation between Gini coefficients and GDP per capita in three time periods, 1820-2000 Gini coefficients and US dollars at 1990 PPP (semi-logarithmic scale). Loess fit with 95% confidence interval.

about USD 2 000; from that point onward, the relation is negative again. For the two post-Second World War periods, the relationship is positive until about USD 3 000, then turns strongly negative, and finally the relationship turns positive again among the countries in the highest income layers. However in both these periods, there are very few observations in the top income region. It is important to notice that for a large income span ranging from a bit below USD 10 000 up until USD 20 000 in the 1980-2000 period, the relation dissolves completely.

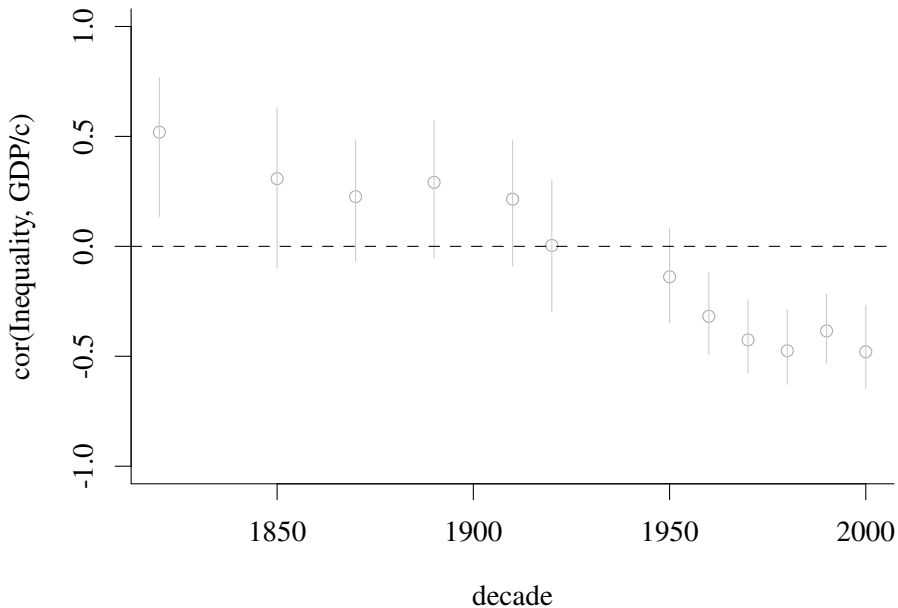


Figure 5.3: Correlation between Gini coefficients and GDP per capita, 1820-2000 Pearson correlation coefficient and upper/lower bounds of 95% confidence interval.

This demonstrates the real complexity of the link between income inequality and GDP per capita. Figure 5.3 shows the correlation of GDP per capita and the Gini coefficient across all the available countries over time. From 1820 until 1910, income inequality appears generally positively correlated with GDP per capita: the wealthiest countries are also relatively more unequal. This relationship reverses at the turn of the century, and after the Second World War the relation turns mostly negative, remaining negative for the entire period until the most recent available

data.

## **5.6. Priorities for future research**

As the discussion of data limitations has suggested, more work on improving the comparability of the data sources and their findings would provide a more solid basis to draw conclusions about income inequality in a country or region or on a global scale. Historical estimates could be much improved by focusing more research on these issues. Whereas for most Western European countries and the Western Offshoots, we have relatively detailed studies that make use of the available historical sources, much more work can be done in this field for many Asian, African and Latin American countries (for examples of recent research see the website of the Global Price and Income History Group at UC Davis: <http://gpih.ucdavis.edu/>). The more recent work in this field also has its problems. Such work requires mobilizing organizational resources on a world scale, orchestrated by international organizations. Inspiration for this type of work could be drawn from initiatives like the International Comparison Program that aims to collect comparative price data and to estimate purchasing power parity globally.

Beyond this effort, further inter-temporal investigation of the relationship between income inequality and social outcomes will help improve our understanding of the mechanisms through which higher levels of income inequality tend to make us all worse-off (Wilkinson and Pickett, 2007). With the increased availability of data, the links between income inequality and other social indicators could be further researched, and extended to other dimensions of well-being. To that end, historical global datasets would need to be constructed and utilized.



## Chapter 6

# Global Absolute Poverty: Present and Past since 1820

by Michail Moatsos<sup>1</sup>

*"There is, perhaps, no better test of the progress of the nation than that which shows what proportion are in poverty, and for watching the progress the exact standard selected as critical is not of great importance, if it is kept rigidly unchanged from time to time."  
(Bowley, 1915, p.213)*

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<sup>1</sup>Author's Affiliation: Department of History and Art History – Economic and Social History, Utrecht University. I wish to thank Marco Mira d'Ercole, Bram van Besouw, Tim van der Valk, Gareth Austin, Alex Kolev, Wouter Ryckbosch, Mark Sanders, Jutta Bolt, Aditi Dixit, Auke Rijpma and Jan Luiten van Zanden for their suggestions, comments and remarks. I particularly thank Bas van Leeuwen for price data on China, who together with Pim de Zwart also shared their digitization of the ILO price data with me; Robert Allen for discussing his method and results, Leandro Prados de la Escosura for all his valuable comments and for sharing his newly updated long run inequality estimates for Spain, Guido Alfani for the inequality data on Sub-Saharan Africa, Christoph Lakner and Prem Sangraula from the World Bank for sending me the underlying CPI dataset the Bank uses for global poverty measurement, and Guus Wieman for his excellent research assistantship. I want to extend my gratitude to the participants at the 2017 Posthumus Conference, the 2017 Economic History Society Annual Conference, and the workshops organized by the editors of this volume in Utrecht and at the OECD in Paris. All analysis has been conducted with R open source statistical computing software (R Core Team, 2018). All remaining errors are my own.

## Abstract

This chapter relies on a global data set on basic commodity prices to provide first estimates of global extreme absolute poverty in the long run using a cost of basic needs approach. For 135 years since 1820, more than half of the global population lived in conditions of extreme absolute poverty. It took another 46 years to cut this rate in half, which only happened as recently as 2001. In the years that followed the reduction of extreme absolute poverty accelerated tremendously, and in 13 more years global poverty rate was halved again. Compared to other available estimates, the world in the 19th century was less poor than we thought of, but relatively poorer in the more recent period. Notably, the total number of people living in conditions of extreme absolute poverty in 1820 stands at 757 million, which is almost identical with the count two centuries later in 2018 at 764 million.

## 6.1. Introduction

Economic growth has spread throughout the planet over the last two hundred years with unprecedented speed, leading to improvements in many well-being indicators, albeit at variable rates (Zanden van et al., 2014). However, economic growth does not necessarily improve the well-being of all people within a country at the same rate, and some may miss the tide altogether. This can be the case when economic inequality within a country rises with, for example, low incomes stagnating and top incomes increasing. However, as argued by Sandel (2012), economic inequality is an issue of entirely different order when it represents differences in the size of yachts (all) people may have, and when it spans from those in extreme deprivation all the way up to those enjoying billions.

This chapter focuses on the evolution of extreme absolute poverty<sup>2</sup> during the period 1820-2018. Only a handful of attempts have been done to estimate global absolute poverty in the short and medium run (Bhalla, 2002b; Sala-i Martin, 2006; Chen and Ravallion, 2010; Ferreira et al., 2016), and even fewer in the long run (Bourguignon and Morrisson, 2002; Zanden van et al., 2011). All these approaches rely on a single value of the poverty line for all countries and for all years, an approach that many scholars find insufficient (Deaton, 2001; Srinivasan, 2009; Reddy and Pogge, 2010; Atkinson, 2016; Allen, 2017).

The goal of this chapter is to provide global, regional and country estimates of a specific measure of absolute poverty for (almost) all present-day

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<sup>2</sup>The definition followed here is focusing on extreme poverty and the terms “extreme poverty”, “absolute poverty” or “extreme absolute poverty” will be used interchangeably.

countries of the world as if they were sovereign in 1820. The first step in this exercise is to choose a definition of poverty. This chapter relies on the cost of basic needs (CBN) approach used by Allen (2017). In this approach, poverty lines are calculated for every year and country separately, rather than using a single global line. The second step is to gather the necessary data to operationalize this approach, alongside imputation methods in cases where not all the necessary data are available. The third step is to devise a method for aggregating countries' poverty estimates on a global scale to account for countries lacking some of the relevant data.

The estimates presented in this chapter show that between 1820 and 2018 the prevalence of absolute poverty across the globe fell from 76% to 10%, the lowest level ever achieved based on our method. This reduction, however, is not distributed evenly throughout the period. It took 136 years since 1820 for our global poverty rate to fall under 50%, then another 46 years to cut this rate in half again by 2001. In the early 21st century, global poverty reduction accelerated, and in 13 years our global measure of absolute poverty was halved again by 2014. Whether this reduction has been sufficient to meet the 50% poverty reduction target set by the first Millennium Development Goal across the developing world between 1990 and 2015 depends decisively upon the treatment of data for pre-1995 China.<sup>3</sup> According to the baseline calculations presented in this chapter, the MDG1 poverty reduction target has been met.

By operationalizing Allen's approach on a long run global scale, this chapter moves beyond the dollar-a-day method, towards an approach that provides a set of transparent poverty lines in every year and every country. Arguably, understanding what a 1.9 dollar at 2011 PPP rates (hereafter simply international dollars) would buy in each country and each year is far from obvious, while the cost of basic needs approach is easily understood by scholars and laymen alike. The cost of basic needs method was recommended by the World Bank Commission on Global Poverty presided by the late Sir Tony Atkinson as an alternative (or complementary) method in monitoring poverty for the needs of the United Nations Sustainable Development Goals (Atkinson, 2016).

The following section describes the methodology in some detail. The sections that follows discuss the historical sources used, assess data quality. I then present key trends in global absolute poverty since 1820, and

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<sup>3</sup>For details on the treatment of pre-1995 China, see the discussion later in this chapter, where two scenarios are considered on how to treat the problem posed by non-market prices. All estimates for pre-1995 China presented throughout this chapter are based on the average of the two scenarios.

comment on the correlation of my poverty estimates with GDP per capita. Finally, I conclude by sketching priorities for future research.

## 6.2. Description of the concepts used

All poverty measures require a yardstick (a poverty line) to distinguish those living in conditions of poverty from the rest of the population. The most well-known poverty line in global poverty measurement is the 1\$-a-day line adopted by the World Bank. This measure was originally expressed in 1985 prices and has been updated since then for each new round of PPP estimates by the ICP. Its origin can be traced to Ravallion et al. (1991b), who gathered data on poverty lines in national currencies for 33 developing and developed countries. In order to make these national poverty lines comparable across countries, Ravallion converted them to a common currency based on PPP exchange rates provided by Summers and Heston (1988). These estimates showed that the poverty line of the group of low-income countries considered clustered around a value of 1 dollar a day.

Several scholars have expressed concerns about the soundness of these global poverty estimates (Deaton, 2001; Srinivasan, 2009; Atkinson, 2016), while others have commented about the large margins of error of those estimates (Atkinson, 2016; Moatsos, 2018a). These criticisms mainly focus on the use of PPP exchange rates to estimate the equivalent income of every person on the planet and, in particular, on the method used to derive the dollar-a-day poverty line. On the first point, the problem is that a single poverty line may not represent equivalent welfare in different countries and across time (Reddy and Pogge, 2010; Subramanian, 2015; Moatsos, 2017a) (Reddy and Pogge, 2010; Subramanian, 2015; Moatsos, 2017a). Reddy and Pogge (2010) argued in favour of a “basic needs approach” in order to resolve the issues raised by the application of PPPs. In response to this criticism, Ravallion (2010b) argued that poor people may adapt their consumption habits following changes in market price, implying that the cost of a fixed consumption basket may exceed that faced by those living in poverty. Allen (2013), while recognising this substitution effect, argued that its effect is overstated, and advocated the use of linear programming techniques (to estimate the least costly basket of goods) to account for this adaptation to price changes.

Estimates of absolute poverty at the global level are generally produced using data on the distribution of household income or consumption expenditure (often adjusted using non-survey information on mean income or



consumption) and a single international poverty line denominated in PPP dollars (Bourguignon and Morrisson, 2002; Bhalla, 2002b; Sala-i Martin, 2006; Chen and Ravallion, 2010; Zanden van et al., 2011; Ferreira et al., 2016). Recently, Allen (2017) estimated absolute poverty using linear programming techniques to identify the cost of a diet sufficient to provide a minimum nutritional content, to which additional expenses for housing, clothing and heating are then added. Allen tests four different setups for such minima: (i) a caloric minimum of 1 700 kcal; (ii) a caloric-protein-fat minima (dubbed CPF) targeting 2 100 kcal, 50 gr of protein and 34 gr of fat; (iii) a “basic diet” that adds half the quantities of additional nutrients recommended by the Indian daily allowances (RDA), namely iron, folate, thiamine, niacin, vitamins C and B12; and (iv) a full course model that adds 6 more vitamins and minerals to the basic diet. Allen concludes that the “basic diet” (option iii) is the more reasonable international standard, since “people eating a CPF diet suffer many nutritional deficiencies”, while the full course model implies unreasonably high quantities of foodstuff to be consumed, and very high caloric intake.<sup>4</sup>

This chapter relies on a “basic diet” poverty line calculated separately for every country and year. However, as the data needed to apply linear programming to estimate a “basic diet” poverty line on a global scale and on the long run are not available,<sup>5</sup> I use a second-best approach, based on the price data from ILO October Inquiry (1924-2008). In this approach, I apply linear programming on the ILO data to first calculate the CPF poverty line, which I then multiply with the multiplier implied by Allen’s results to get a proxy of the “basic diet” poverty line.<sup>6</sup> In addition, when price level data from ILO are not available for a particular country and year, I follow

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<sup>4</sup>According to Allen’s calculations, the CPF poverty line for developing countries is 1.84\$/day, on average, which implies that the 1.9 dollar-a-day poverty line used by the World Bank and United Nations to monitor global absolute poverty is too low, as “people eating a CPF diet suffer many nutritional deficiencies” (Allen, 2017).

<sup>5</sup>As Allen’s estimates are only for 2011, and he uses the 2011 ICP price data.

<sup>6</sup>Using Table 11 from Allen (2017). This is done in two steps: 1) one multiplier is used to bring the cost of the food component of the CPF poverty line to the level of the basic diet; and 2) another multiplier is used to account for non-food items, based on the share of food component in the total consumption basket of the basic diet (Table 12 in Allen (2017)). In our approach, both multipliers are a function of GDP per capita (based on the estimates by Bolt and van Zanden, 2014). In the calculations of those multipliers France is excluded, as the price for wheat flour used by Allen (at less than 0.5 euro per kg in 2011) appears very low relative to the ILO price data used here (around 1.5 euro for 2011). See the on-line Appendix for additional information on these multipliers. This approach is not sensitive on the between-countries differences in heating requirements. For a discussion of this issue see Moatsos (2017a,b); Allen (2017).

the general practice, common to the dollar-a-day approach, of using the national consumer price index (CPI) to extend over time my estimate of the basic diet poverty line. The types of expenses considered by the options (i)-(iii) above refer only to the food expenses. To estimate the costs of the final “basic diet” poverty line, additional coefficients expressing the share of food in total household consumption (coefficients that change with the GDP per capita of each country) are estimated from Allen’s results in order to move from a “food” to a “full-line” approximating the expenses that people living in absolute poverty in each country and year have to incur.

### 6.3. Historical sources

Four main types of data are required to produce global estimates of absolute poverty with a cost of basic needs approach: (i) a set of prices for different consumption goods (supplemented by general price indices when needed); (ii) a set of data on the distribution of consumption or income in each country; (iii) a set of population data; and (iv) a set of nutrients to be assigned to the various foodstuff in the price database. The nutrient contents are taken from the USDA website<sup>7</sup>, while the population data are from the Maddison project (Bolt and Zanden van, 2014) complemented, whenever necessary, by data from the United Nations World Population Prospects.<sup>8</sup> The sources for the remaining data are discussed below.

#### Prices from the ILO October Inquiry

Since 1924 the International Labor Organization (ILO) collected prices for basic foodstuff and necessary consumables such as bread, rice and fat products in types typically purchased by working families. This data collection started with a small set of 16 capital cities surveyed every October, which grew to cover 130 countries by 1967, dropped to 79 countries in 1983 and then increased again to about 120 countries. The product listings included 15 items in the early years that incrementally increased to cover 39 main products by 1984. The ILO stopped the collection of prices in 2008 due to a re-organization of its activities.<sup>9</sup>

<sup>7</sup><https://ndb.nal.usda.gov/ndb/>, last accessed 19/9/2019.

<sup>8</sup><https://population.un.org/wpp/>, last accessed 12/9/2019.

<sup>9</sup>The post-1984 price data were downloaded from the ILO’s website, while the 1924-1984 data were scanned from various publications at the ILO document repository. The new version of ILO-STAT does not contain the price data any more, while the document repository with all available price data in pdf format can be mainly found at <https://www.ilo.org/public/libdoc/ilo/>

A long process of digitizing these price data has been undertaken by de Zwart et al. (2014) using manual entries and Optical Character Recognition (OCR) techniques; in addition, I undertook an independent digitization using a manually assisted OCR approach. When the two approaches provided different values, I have investigated for possible errors; when the two approaches gave the same result. I assume to have valid digitisations.

The October Inquiry commodity price dataset offers data points spanning a period of at least 80 years for 18 countries, and more than 50 years for 108 countries. These data were reported to ILO by the national statistical agencies of each country, which were instructed to report prices that were relevant for working families. This makes this dataset particularly useful for the calculation of the costs of basic needs poverty lines. As all historical data, the ILO dataset has its problems. For example, one needs to be careful with currencies before and after a currency redenomination takes place in a country.<sup>10</sup> Another issue is that the October Inquiry price dataset refers to prices in a single month, implying that, when inflation is high, these price data may not be representative of the full year. For high inflation years, e.g. in Brazil or Zimbabwe, I relied on changes in average CPI to estimate the poverty line, rather than on the ILO price data. In addition, some ILO entries are clearly too low or too high, by a couple of orders of magnitude, relative to the price for that country in a close year; those prices were also removed from the final dataset.<sup>11</sup>

Also, prices for all products are not reported for all countries at all times. This means that one needs to impute these missing data using either the CPI index of that country or, when this is also not available, the evolution of the similar prices in the ILO dataset.<sup>12</sup> Such an imputation, however, may result

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P/09615/.

<sup>10</sup>Since price information in the ILO data are expressed using the currency denomination prevailing at the time (nominal prices), information on changes in currency denomination is required to denominate all prices in the currency used today. This was done using the dataset on history of currencies provided by Global Financial Data, Global History of Currencies dataset downloaded from [https://www.globalfinancialdata.com/news/GHC\\_Histories.xls](https://www.globalfinancialdata.com/news/GHC_Histories.xls) and accessed on 16, July 2014; additional information on currency redenomination was used for the more recent period based on information available at the websites of national central banks, and collected on Wikipedia pages for local currencies.

<sup>11</sup>See the Appendix for more details.

<sup>12</sup>A variety of CPI sources were used, giving priority to the PovcalNet CPI data, followed by other source in order of preference: World Bank WDI data, IMF CPI data, Jordà et al. (2016) CPI data, Clio Infra Consumer Price Index dataset from the Clio Infra project website (dataset downloaded from <https://clio-infra.eu/Indicators/Inflation.html> on 12, August 2015), Balkans CPI (historical CPI series from Balkan countries: South-Eastern European Mone-

in prices that are distant from those paid by working families. For example, prices of the cheapest product providing a given number of calories may follow a different trajectory than the average CPI of a country, and after say 10 years one may have a price much higher or much lower than the unobserved one. This is an important limitation of our approach.

The same applies for years outside the 1924-2008 period, where the cost of the food component is extrapolated using available consumer price indices. This imputation rests on the assumption that, on average, the cost of the food component does not substantially diverge from the average CPI. This is a strong assumption. More work to gather detailed price data will be required to extend the coverage of our price dataset to the full time period covered by this chapter.

Nevertheless, the use of detailed nominal prices brings the methodology of measuring absolute poverty one step closer to the experience of people living in poverty across the world. It removes one layer of assumptions, compared to other approaches that rely on one single poverty line expressed in PPPs, or that rely on a CPI index for moving the poverty line in time for about 20, 50 or 170 years (Bourguignon and Morrisson, 2002; Bhalla, 2002b; Sala-i Martin, 2006; Chen and Ravallion, 2010; Zanden van et al., 2011; Ferreira et al., 2016).

Panel A in Figure 6.1 shows the number of CPF food components calculated from the complete ILO data, with dark colour indicating non-imputed data for the food items selected by the linear programming. Panel B shows the same information expressed as percentages of global population covered by those baskets. Direct estimates of poverty lines based on ILO data only start in 1924, covering around 14% of global population at the time. For the period 1950-2008, the average population coverage is 78%. Using CPI extrapolation, the average population coverage for the period 1884-2018 is 78%, while for the period before 1884 population coverage drops to 23%.

### **Consumption and Income Distributions**

To compare with the global poverty estimates published by the World Bank, our calculations rely on the data of the distribution of consumption and income available via World Bank's PovcalNet. While the combination of consumption and income data obviously reduces cross-country comparabil-

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tary and Economic Statistics from the Nineteenth Century to World War II, published by: Bank of Greece, Bulgarian National Bank, National Bank of Romania, Oesterreichische Nationalbank, 2014, Athens, Sofia, Bucharest, Vienna) and the ILO general and food CPI index.

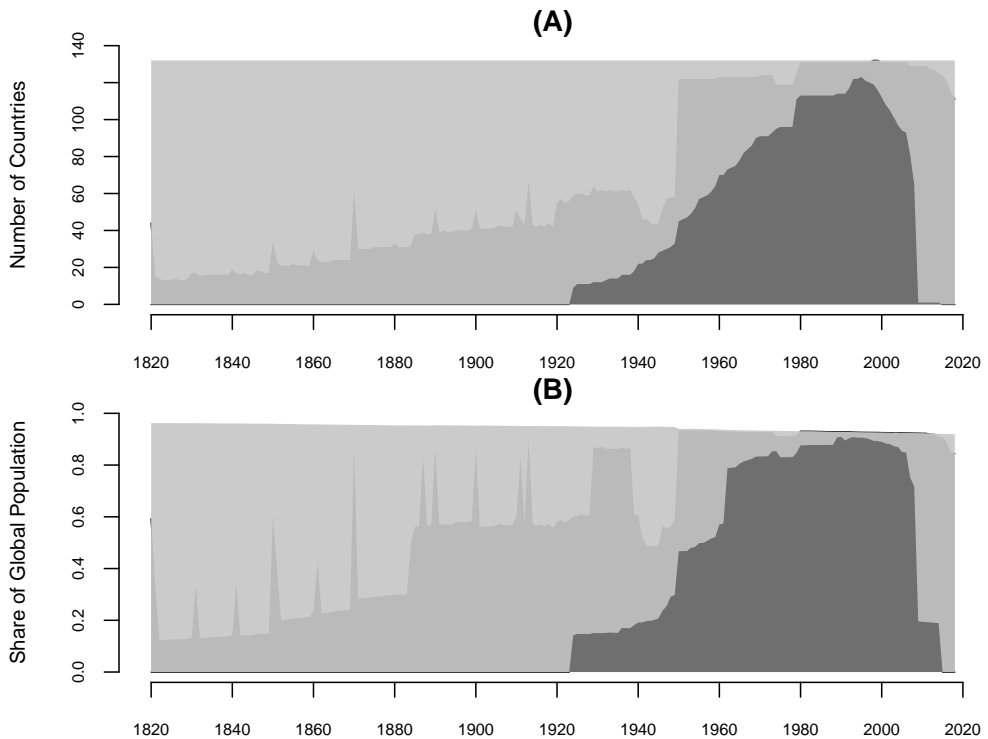


Figure 6.1: Note: Panel A shows the number of food baskets calculated in this chapter based on different methods: the original ILO data (in dark gray), the costs of food baskets imputed via CPI (in gray), those based on interpolations and regional extrapolations (in light gray). (See the section on imputations for details). Panel B shows the share of the global population covered by these estimates. The spikes in population coverage are due to China and India (large spikes) or India (small spikes) in 19th century, and China in the early 20th.

ity in the PovcalNet dataset, I do not try to correct for this in order to preserve comparability between my estimates and those produced by the World Bank. The distributional data in PovcalNet cover the post 1980 period.

Other sources of distributional information need to be used for the years not covered by PovcalNet. These sources typically provide values of the Gini index of the entire distribution, rather than the distribution itself. Thus, a method is required to convert this single statistic into an entire distribution, in order to estimate the share of population with income or consumption below a poverty line. To do this, I rely on the log-normality assumption, which converts a Gini index to a full distribution that follows a log-normal shape (Aitchison and Brown, 1957; Zanden van et al., 2013).<sup>13</sup>

In summary, for the most recent period, I use the distributions provided by PovcalNet. For the period between 1950 and the year when PovcalNet coverage begins for a particular country, I use a variety of sources<sup>14</sup> that for many countries contain household income surveys typically conducted by national authorities.<sup>15</sup> Preference is given to distributions of disposable income, followed by those distributions capturing gross (i.e. pre-tax) income, and finally distributions that do not specify the exact type of income they capture; in cases when several estimates of comparable quality are available, I take their average. I rely on databases providing synthetic Gini estimates<sup>16</sup> to provide information on the evolution of the Gini index between observations from the aforementioned sources.<sup>17</sup> For the period prior to 1950,

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<sup>13</sup>Beyond the PovcalNet distributional data (mostly based on consumption), the distributional data used in this chapter are all income based. The log-normality assumption used to convert Gini to a full distribution does not work satisfactorily when applied to consumption data, but works well enough for income-based distributions (Lopez and Servén, 2006).

<sup>14</sup>Those sources are: SEDLAC, STATCAN, US CENSUS data, UNU-WIDER WIID (version 19 December 2018), OECD Income Inequality Database (accessed 11 February 2019), All The Ginis Dataset (version February 2019), EUROSTAT (last update 31 January 2019), GiniProject (version September 2013), the Luxembourg Income Studies Database, UK Institute for Fiscal Studies (Living Standards, Inequality and Poverty Spreadsheet), and Chartbook of Economic Inequality (May 2017 edition, (Atkinson et al., 2017)).

<sup>15</sup>As opposed to indirect estimates based on social tables or other methods (e.g. based on the relation between the coefficient of variation of height and income inequality (Moradi and Baten, 2005; Zanden van et al., 2013)). In addition to the scarce availability of data per se, the underlying methodologies and concepts used for carrying out a survey vary between countries and periods. Moreover, changes in the concepts and methodologies introduce structural breaks in the series for a given country.

<sup>16</sup>Solt (2016) and the Estimated Household Income Inequality Data Set (EHII) V2017 v.1 from Texas University.

<sup>17</sup>The growth pattern implied by the evolution of the synthetic index is used to impute the Gini values between actual observations from other sources, with values that follow the same growth pattern as the synthetic index. When this is not possible poverty rates are calculated using the available

inequality data are sourced from Zanden van et al. (2013), and other studies (Bolt and Hillbom, 2016; Alfani and Tadei, 2017; Prados de la Escosura, 2008; Kang, 2001).

### **Estimating unobserved household mean income**

After having derived an estimate of the distribution of income or consumption in a country, one needs to “pin down” the dispersion of the distribution around a mean in all cases where this information is not available in the source used. Information about this mean can be drawn from either National Account statistics, or from the same household survey that provides information about its distribution. Starting off from PovcalNet provides an advantage in this respect, as the values of the household survey mean are known, and can be extrapolated back in time using consumption or GDP data.

Deaton (2001, p.132) reports that, in the case of India, the ratio of mean household consumption measured by System of National Account (SNA) and by the main survey on the distribution of household expenditures (the National Sample Survey) fell from almost unity in 1950 to about 50% by late 90s. Ferreira et al. (2015) correct for this divergence between mean consumption growth from the surveys and from the National Accounts (by using 87% of the SNA consumption growth for all countries, 51% for India and 72% for China). The same approach is used here, but we also take account of the time effect noted by Deaton. Therefore, I apply the conversion factors of Ferreira et al. (2015) for 2000, which I then linearly extrapolate to assume a value of 1 by 1950, implying the same growth rates for mean income in survey and SNA prior to 1950.

### **Imputations**

To generate estimates of absolute poverty across the globe, imputations are needed for missing countries and years in order to avoid abrupt changes in coverage. In this chapter, imputations are based on the change in the average poverty rate of the countries in that region for which there are available data.<sup>18</sup> This approach avoids the downward bias associated with the greater

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Gini indices at both ends, and then their weighted average is taken; with the estimates based on the closer Gini data point being linearly assigned more weight.

<sup>18</sup>In this calculation, only poverty estimates from countries that are available in both years and are not a result of regional imputation or interpolation are used.

availability of data for rich countries in historical times.<sup>19</sup> In addition, when enough data are available for a country at two distant points in time, the poverty rate between those two points is linearly interpolated – instead of regionally imputed. Such an approach is applied mostly to data during the 19<sup>th</sup> century.<sup>20</sup>

## 6.4. Data Quality

Table 6.1 shows my assessment of the quality of poverty estimates for the 8 world regions for a selection of years, in terms of credibility, accuracy and comparability. Among these dimensions, the degree of credibility is relatively high throughout the period, while the degree of accuracy is lower especially when price data refer to non-market economies (China and former Soviet Union among others); in these cases, no goods may be available at these administrative prices, hence violating a basic assumption of the cost of basic needs approach.<sup>21</sup> A similar problem arises when the average consumer price index is used instead of detailed product prices. This issue however is easier to treat, simply with more data collection in the future. With these caveats in mind, my assessment is that the degree of comparability is more or less sufficient, in spite of differences across countries in the underlying income distributions data.

All the basic needs poverty lines we estimate are shown in Figure 6.2. These poverty lines are based on linear programming to derive to the CPF

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<sup>19</sup>The World Bank takes a different route assuming (regardless of the set of countries for which data are available) that countries without data have the same poverty rate as the rest of the region. This is strong assumption that I attempt to relax here. The countries used for regional extrapolation in the 19th century going back to 1820 are: Japan, for East Asia; South Africa (and Ghana up to 1870) for Sub-Saharan Africa; Jordan, Lebanon, Egypt, Iran, Morocco, Tunisia, Syria and Turkey for Middle East and North Africa; Denmark, Norway, Austria, Ireland, Italy, Netherlands, France, United Kingdom, Finland, Sweden and Portugal for Western Europe; the United States, Canada and Australia for the Western Offshoots; Argentina, Brazil, Chile, Colombia, Jamaica, Mexico, Peru, Uruguay and Venezuela for Latin America and Caribbean; Indonesia, Sri Lanka, Myanmar, Malaysia, Nepal, Philippines, Thailand, (and India up to 1821) for South and South East Asia; Poland for Eastern Europe and former Soviet Union. More countries are used for imputations later in 19th century and in 20th and 21st centuries.

<sup>20</sup>Those linearly interpolated estimates are not used for the regional imputation described previously. Moreover, going back in time and when no other information on inequality is available, the last available Gini index is used to pin down an estimation for the country level poverty rate.

<sup>21</sup>Once a cheap product is in shortage, a more expensive one should be used by the linear programming. Such information is lacking at the moment. In the case when the low-price products are indeed available and are purchased by those living in poverty, then those prices are used for calculating the costs of a basic needs poverty line.



Table 6.1: Quality of data on poverty by region and year; 1, High quality; 2, Moderate quality; 3, Low quality; and 4, Estimates. For details about China (which represents the vast majority of the population in East Asia) see the relevant results section.

YEAR	Western Europe	Eastern Europe & f. Soviet Union	Western Off-shoots	Latin America & Caribbean	Sub-Saharan Africa	Middle East & North Africa	East Asia	South & South-East Asia
1820	4	4	4	4	4	4	4	4
1870	4	4	4	4	4	4	4	4
1920	3	4	3	4	4	4	4	4
1950	2	4	2	2	2	2	4	2
1980	1	4	1	1	1	1	4	1
1990	1	4	1	1	1	1	4	1
2010	1	1	1	1	1	1	1	1

line, to which relevant multipliers are applied for obtaining the basic diet poverty line and the non-food component. The dark blue points refer to the poverty lines estimated based on the ILO data,<sup>22</sup> while the light blue points are those extrapolated based on CPI.<sup>23</sup>

When looking our poverty lines throughout historical times, the United Kingdom has the highest poverty line in PPP terms at just below 5\$/day during the long 19<sup>th</sup> century, while thereafter Switzerland has on average the highest poverty line (Figure 6.2). The poverty line for the United States is very close to the 1.9\$/day until WWII, increasing thereafter.<sup>24</sup> India has a poverty line that is very close to the 1.9\$/day, for the entire period. Mexico begins with a poverty line slightly below 1.9\$/day, falling below 1\$/day in the early 1980 but gradually returning to 1.9 by 2018. In the case of Russia, the poverty line shows a huge increase following the dissolution of the Soviet Union in 1991. The poverty line is very volatile in both Nigeria (with a number of spikes bringing its value at about 3\$/day, and with an

<sup>22</sup>Thus, include interpolations and extrapolation of prices using CPI or the evolution of prices of similar products within the ILO dataset.

<sup>23</sup>Both as a –generally increasing– function of real GDP per capita, see the Appendix for more details.

<sup>24</sup>During the last few years in the period both Swiss and US poverty lines flat out at a constant PPP level. This is because the CPF cost is fixed in PPP terms, and the applied multipliers are and remain at their maximum.

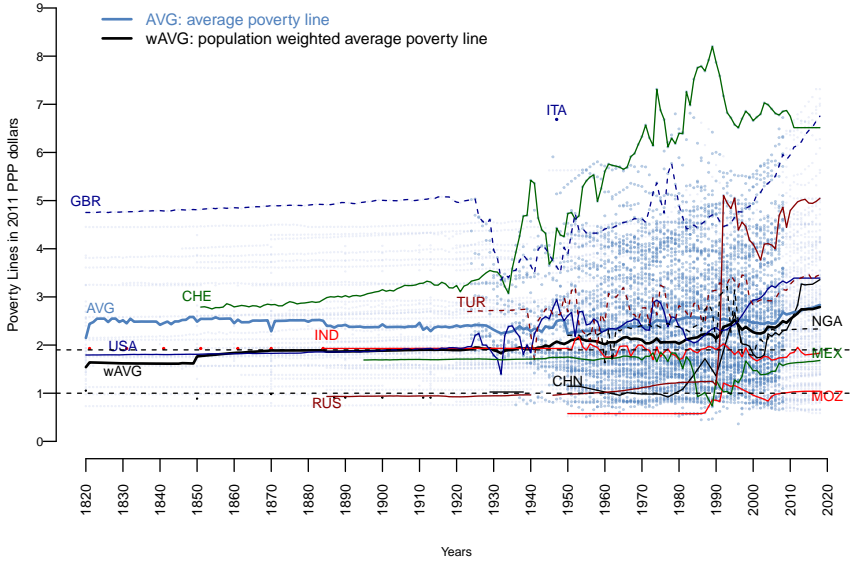


Figure 6.2: Global Poverty lines distribution per year, selected countries are traced through, along with the simple- and the population weighted average poverty line per year. Only one estimate for Italy is highlighted to indicate which country has this peak value in 1947.

average value clearly above the 1.9\$/day) and Turkey (starting at 2.7\$/day in 1924, and rising to 3.5\$ by 2018). The poverty line is lowest in Malawi and Mozambique, at around 0.6\$/day.<sup>25</sup>

On average, these lines for absolute poverty hover around 2.5\$/day for almost the entire period, with only the years after 2010 showing a clear increase, reaching a maximum of 2.8\$/day in 2018.<sup>26</sup> The population weighted average poverty line has, however, a different trajectory. Starting from a level slightly below 1.9\$/day in early 19<sup>th</sup> century, it is broadly

<sup>25</sup>Here the implications of using multipliers to estimate the non-food component, and the richer basic diet, instead of using original data, are becoming somehow evident. If the food component is at very low levels, then the multiplier may underestimate the additional costs. Likewise, when the initial CPF food component is relatively high, then the multipliers most likely overestimate the additional costs.

<sup>26</sup>27 A low value of 2.16\$/day is observed in 1820, mostly due to different coverage than most of the other years in the 19<sup>th</sup> century. A similar reduction is observed in 1870 for the same reason.

constant from 1850 to the early 1940s, increasing thereafter to 2.8\$/day by 2018. It is clear that the values of these poverty lines vary considerably even for the most recent years, ranging in 2018 between 1\$ and 7\$, which is in line with the findings of Allen (2017) and Hirvonen et al. (2019).

## 6.5. Main highlights of trends in global poverty

The figures in this section show the evolution of absolute poverty rates across the globe based on the cost of basic needs method, alongside those based on other methods. Generally, four types of poverty estimates are drawn. The main line, shown in dark gray, is the poverty rate based on the CBN methodology used in this chapter. The other lines correspond to the 1.9\$/day-line (noted as DAD) and the 1.9\$/day poverty line applied to distribution data centred on GDP per capita as mean value of the distribution (shown as GDP1.9 prior to 1979, i.e. before the PovcalNet data).<sup>27</sup> Estimates of absolute poverty at the world level from Bourguignon and Morrisson (2002) are also included in Figure 6.3.

### Global Poverty Estimates

Both the CBN and the DAD approaches suggest a bleak picture of absolute poverty in 1820, at 76% and 79% respectively (Figure 6.3). Bourguignon and Morrisson (2002), with less available data and using 1985 PPP exchange rates, estimate a higher value at 84%.

According to these measures, roughly three-quarters of the global population in 1820, about 756 million people, could not afford a tiny space to live, food that would not induce malnutrition, and some minimum heating capacity. This total number of persons living in absolute poverty is almost identical to the estimate for 2018, which stands at 764 million people. For the entire period between 1820 and 2018 this total count of the number of people living in absolute poverty reaches a maximum of 2 billion in 1995.

By 2018 global absolute poverty dropped to 10%. Based on our methodology, the global poverty rate fell below 70% in 1873, and below 60% by 1897; after that, it takes much longer to drop below 50% by 1955, then

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<sup>27</sup>In other words, the difference between GDP1.9 and DAD is fully attributable to the effect of substituting GDP per capita with the estimated household mean income, and the difference between DAD and CBN lines is fully attributable to the effect of different poverty lines. More detailed estimates on a per country basis, and an exposition of some methodological details left out from the main text can be found in the Appendix.

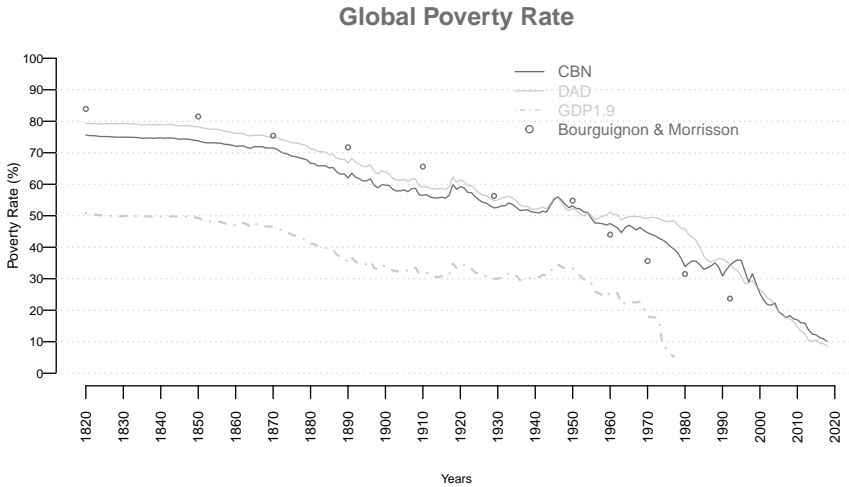


Figure 6.3: Absolute poverty around the world; share of people living in conditions of absolute poverty globally, based on different estimates.

much faster to drop below 40% by 1977. In another 20 years global absolute poverty drops below 30% in 1997, while the 20% barrier is passed in 2005. The fastest drop in the entire period takes place between 1995 and 2000. During the World War years (I or II), absolute poverty rates show a small increase at the global level.

The global total count and the geographical distribution of those living in conditions of absolute poverty across the globe is shown in Figure 6.4. East Asia accounted for the largest share until 1962, but was overtaken by South and South-East Asia thereafter. The upward trend in the global population living in absolute poverty (shown by a dotted line) was interrupted decisively only in 1995, with a few other noticeable but transitory corrections in 1917, 1947 and 1976. At its peak in 1995, the total number of people living in absolute poverty was 2.7 times that of 1820. Both the increased in total number of poor people and its decrease following the two World Wars are clearly visible. The sharp increase in 1950 corresponds to the inclusion of several Sub-Saharan Africa countries from year point onward.

Table 6.2 provides an overview of absolute poverty rates across world regions in some benchmark years throughout the period and in 2018. The regions with the highest (lowest) poverty rates in a given year are marked

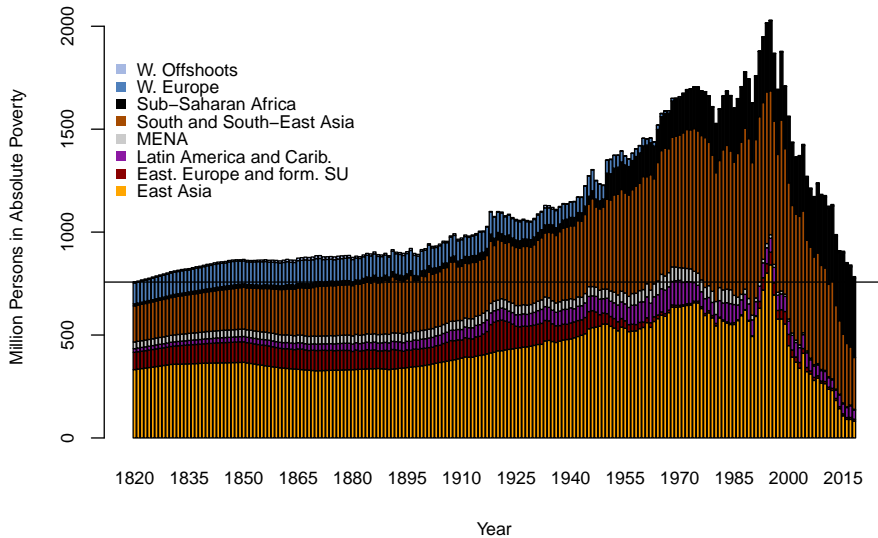


Figure 6.4: Geographical distribution and total count of people living in conditions of absolute poverty across the globe, 1820-2018; the horizontal line corresponds to the total population in absolute poverty in 1820.

in gray (light gray). Based on these measures, Eastern Europe and the former Soviet Union achieved the largest reduction in absolute poverty, from 91% in 1820 to 2% in 2018. Sub-Saharan Africa, which started from the same level in 1820, stands at 37% in 2018. Western Europe in 1820 had a higher prevalence of absolute poverty (73%) than South and South-East Asia (69%).

Table 6.2: Global Poverty in World Regions (in percent). Gray (light-gray) background color indicates highest (lowest) poverty rate for that year (close ties allowed).

YEAR	Western Europe	Eastern Europe & f. Soviet Union	Western Off-shoots	Latin America & Caribbean	Sub-Saharan Africa	Middle East & North Africa	East Asia	South & South-East Asia
1820	73	91	55	85	91	79	77	69
1850	65	84	28	84	95	75	80	69
1870	59	68	31	80	93	72	80	74
1900	41	43	9	74	91	65	76	66
1920	38	63	3	61	87	61	77	62
1950	21	19	1	45	70	40	82	67
1960	11	8	0	45	67	41	66	69
1970	2	2	0	42	62	33	64	64
1980	0	3	1	12	63	25	46	50
1990	0	1	1	17	58	7	37	47
2000	0	13	1	12	50	3	29	35
2010	1	3	1	8	41	1	17	23
2018	1	2	1	7	37	1	5	10

Table 6.3 presents absolute poverty rates for the 25 countries that are the focus of this book, showing estimates with a 10-year frequency, as well as those for 2018. In 1820, no country has a poverty rate lower than 50%, with Russia having the highest at 98% and the United States the lowest at 52%. The poverty rate in the United Kingdom, at 80%, is similar to that of several western countries, while that in Poland, India and Argentina are around 65%, and China is at 76%. Brazil, Japan, Turkey, Indonesia, Kenya and Nigeria have all rates at or above 90%. By 1920, the situation changes drastically for all western countries in Table 9.3, as well as in Egypt and Argentina, with improvements of more than 30-40 percentage points, and of more than 60 points in Canada and Poland. However, other countries like Kenya, Turkey and China, have stagnated or worsened relative to 100 years before, while Brazil, South Africa, Japan and Indonesia show some improvement. By 2018, most countries have attained very low rates of absolute poverty, with the exception of Kenya and Nigeria that (where it is still above 60%). Based on our estimates, absolute is still substantial in South Africa (at 20%) as well as in India and Indonesia (at around 10%).

Table 6.3: Cost of Basic Needs Global Poverty rates of 25 focus countries.

Years	GBR	NLD	FRA	DEU	ITA	ESP	SWE	POL	RUS	AUS	CAN	USA	MEX	BRA	ARG	EGY	TUR	KEN	NGA	ZAF	CHN	JPN	IND	IDN	THA
1820	80	75	77	66	75	83	86	64	98	87	74	52	86	91	63	60	90	92	92	86	76	91	65	96	82
1830	78	74	75	64	75	81	83	56	90	69	69	43	87	92	56	56	90	88	88	82	76	93	65	97	82
1840	78	67	72	63	74	78	82	58	90	45	58	34	87	92	48	52	89	93	93	86	77	95	65	97	82
1850	69	64	67	59	75	74	78	54	85	28	44	26	87	93	41	48	88	96	96	90	78	98	65	99	81
1860	68	65	63	55	75	67	72	36	70	15	41	28	89	90	45	44	88	89	89	83	78	97	67	98	81
1870	55	63	65	53	76	71	71	30	65	17	35	31	84	87	51	40	87	98	98	83	77	97	70	98	81
1880	48	56	61	45	77	52	68	17	49	7	35	18	77	89	43	36	86	70	70	54	76	96	68	97	75
1890	35	47	53	31	74	51	66	7	46	3	28	9	70	88	23	32	85	90	90	67	73	97	63	97	69
1900	32	47	51	25	72	53	55	3	31	5	19	9	66	95	21	27	84	100	100	77	74	92	61	95	68
1910	35	44	47	24	65	46	46	2	27	4	9	8	60	90	17	23	82	100	100	69	77	90	51	93	67
1920	33	36	45	32	45	51	34	1	70	4	10	2	56	76	18	21	92	100	100	70	76	83	57	90	69
1930	20	19	51	22	47	42	19	1	27	1	7	4	56	77	12	18	78	97	97	68	77	80	48	86	71
1940	6	12	49	14	40	42	19	0	11	0	2	1	50	89	6	16	66	100	100	52	79	64	53	85	68
1950	2	8	30	21	37	34	4	0	3	0	0	1	37	72	2	14	62	81	99	40	84	73	61	91	67
1960	4	5	16	5	20	20	2	3	0	0	0	0	30	73	1	14	51	74	94	38	73	23	66	90	60
1970	0	0	0	2	3	5	1	0	0	0	0	0	24	76	0	12	45	66	94	24	75	2	67	73	40
1980	0	0	0	0	0	0	0	0	0	0	0	1	6	11	2	1	32	62	95	15	53	0	49	40	32
1990	0	0	0	0	0	0	0	0	0	1	0	0	3	23	2	0	12	54	72	29	42	0	47	41	18
2000	0	0	0	0	0	0	0	1	18	1	1	1	5	12	9	0	8	65	71	28	33	0	32	42	10
2010	1	0	0	0	2	1	1	1	2	1	0	1	3	8	2	0	5	61	64	18	19	1	23	25	3
2018	1	0	0	0	3	2	1	0	2	2	1	1	2	7	0	0	2	61	62	21	5	1	9	11	1

### Poverty Estimates in World Regions

Absolute poverty in Western Europe (Figure 6.5) fell continuously for the entire period until the late 1970s, when it is almost zero. This trend is interrupted twice by both World Wars, with the impact of World War II being much more pronounced. At 41%, the post WWI peak is roughly 5 percentage points higher than the minimum achieved 1913. The post-WWII peak, at 35%, is roughly 10 percentage points higher than the minimum in 1939.<sup>28</sup> Since 2003, absolute poverty rates in Western Europe experienced an upward creep, to a level slightly above 1% in 2015. The difference in absolute poverty between the CBN and the DAD estimates for Western Europe is substantial, at around 15 percentage points for most of the pre-WWII period, possibly reflecting higher prices for more expensive services such as rents in the CBN estimates.

The largest share of the total count of absolute poverty for the region in 1820 (101 million) comes from France (24 million), followed by the United Kingdom (17), Germany (16.5), Italy (15) and Spain (10). By 1900, Italy accounts for 24 million persons in absolute poverty, followed by France (20), Germany (13.7), United Kingdom (13) and Spain (10). In 2018, Italy accounts for 1.7 million to the 4.3 million absolute poor in the region, followed by Spain (0.9), United Kingdom (0.7), Germany (0.2) and Greece (0.2).

Figure 6.6, which describes the evolution of poverty rates for Eastern Europe and former Soviet Union, highlights three periods of abrupt changes: two after each World War and one after the dissolution of the Soviet Union. In 1820, this region had a poverty rate of 91%, practically the same rate as Sub-Saharan Africa in the same year. A period of steady reduction starts in 1830, bringing it to 84% by 1850. In 1851 a strong – although not entirely uninterrupted – poverty decline starts, which is faster than the one realised in Western Europe in this period, bringing the poverty rates to 38% by 1913. A remarkable increase in absolute poverty took place during WWI, which brings poverty to a high of 64% in 1921. A period of remarkable poverty decline starts from 1922, which bring absolute poverty to 1% in 1990, after a strong but temporary increase after WWII.<sup>29</sup> Absolute poverty increases again after the dissolution of Soviet Union, hovering at 10-15% until 2000, and then continuously declining to 2% by 2018.

In terms of country level contributions to the regional total, Russia was the biggest contributor in 1820, with approximately 31 million, followed by Ukraine

<sup>28</sup>In both World War cases a methodological problem presents itself: if and how should the death toll of the wars be counted in the poverty statistics. Especially due to the acceleration in poverty reduction in the period after the peak. It may well be a misuse of statistical information or a demonstration of wrong accounting to conclude that a positive long run impact of war on poverty exists.

<sup>29</sup>As noted above, however, this period is particularly problematic due to the non-market nature of product prices, therefore caution is advised for the interpretation of these estimates.



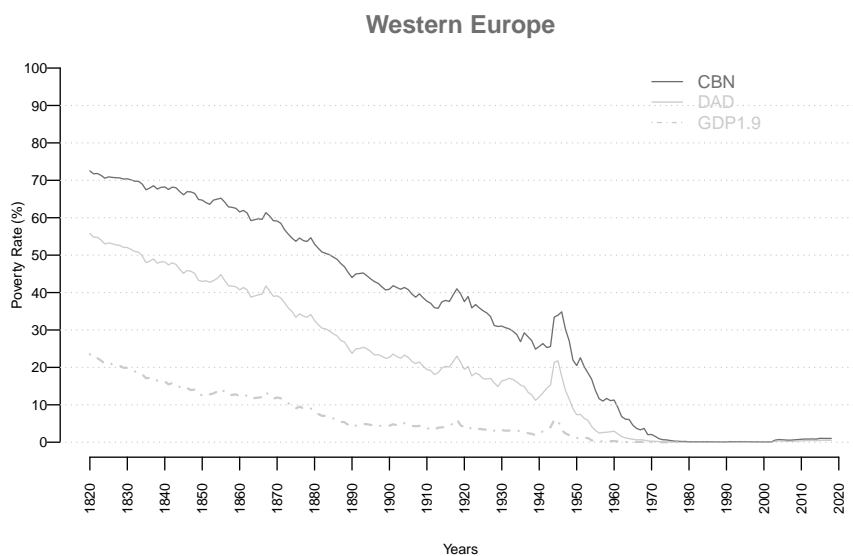


Figure 6.5: Poverty rate for people living in conditions of absolute poverty globally defined for the region of Western Europe, in comparison with other estimates.

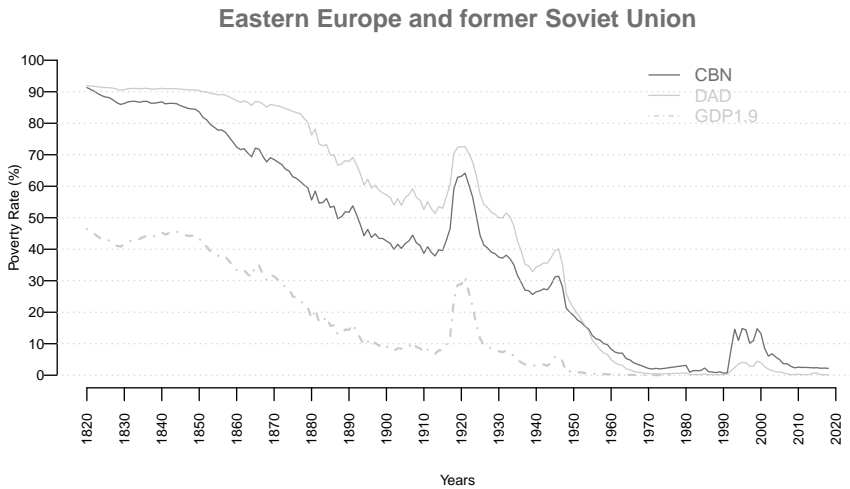


Figure 6.6: Poverty rate for people living in conditions of absolute poverty globally defined for the region of Eastern Europe and former Soviet Union, in comparison with other estimates.

(11), Poland (6.7), Romania (6.4), and the Czech Republic (5). By 1990, Ukraine contributes 24 million (almost its entire population), Russia (22), Romania (5.5), the Czech Republic (5.2), and Bulgaria (2.8).<sup>30</sup> In 1995, which is the peak year after the Soviet Union dissolution, Russia contributes 33.5, followed by Ukraine (8), Moldova (2), Armenia (1.2) and Poland (0.7).

Figure 6.7 shows the evolution of absolute poverty in South and South East Asia, a region that (population wise) is dominated by India. Prior to 1890s data are very scarce and only available for a few countries in a few benchmark years; the linear interpolations for the best part of 19<sup>th</sup> century are evident in the figure. In any case, available data show a poverty rate of 69% in 1820, a level more or less unchanged until 1890s. A volatile period between 1884 and the late 1920s bring absolute poverty to a minimum of 54%. The upward trend that follows takes the poverty rate to 71% in 1953, a higher level than the one recorded in the 1820s. Since then, absolute poverty has declined to a low of 10% in 2018, interrupted by a temporary surge in 1998, when the poverty rate climbed to 46%.

In terms of absolute contributions, India accounts for 136.6 million people in

<sup>30</sup>By 1900 Poland has relatively low levels of absolute poverty at around 3%. This low value is partly attributable to the very low poverty line just above 1\$/day in that period, and partly to its GDP level and GDP/HHS mean ratio.

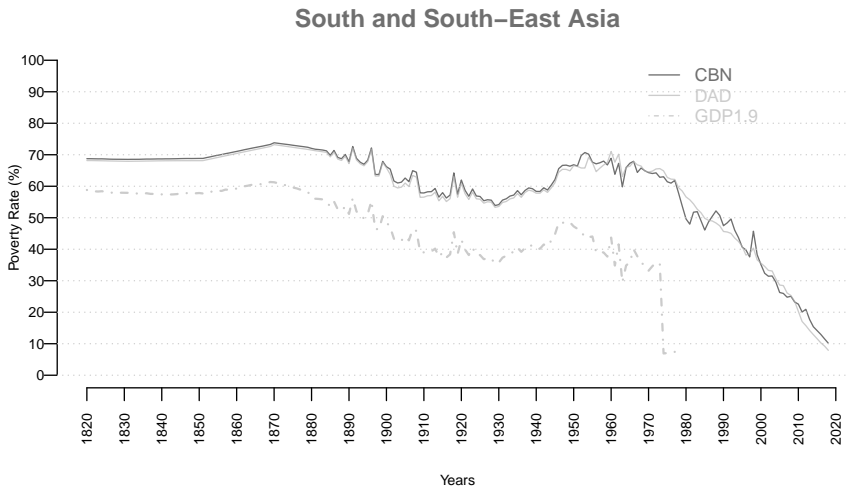


Figure 6.7: Poverty rate for people living in conditions of absolute poverty globally defined for the region of South and South East Asia, in comparison with other estimates.

global poverty counts in 1820, Indonesia contributes 17.3 million, followed by Thailand (3.8), and Nepal (3.2). By 1950, India contributes 217.9 million people in global poverty counts, followed by Indonesia (75.1), Bangladesh (30.1), Pakistan (28.3) and Myanmar (17.4). Finally, in 2018 India contributes 126.9 million people, followed by Bangladesh (55.2), Indonesia (29), Pakistan (11) and Philippines (6.4).

Figure 6.8 shows the evolution of absolute poverty in East Asia.<sup>31</sup> East Asia is the only region where absolute poverty reached its peak in the 20th century, at 83% in 1949. The poverty reduction during the post WWII period stalled in 1958, with a local maximum of 69% in 1961, resuming its fall after 1969, to a minimum of 37% in 1990. Since then, absolute poverty increased to a new peak of 59% in 1995, only marginally lower than the estimate for Sub-Saharan Africa in the same year, before falling to an overall minimum of 5% in 2018.

As expected, China is by far the largest contributor in absolute terms throughout the period. In 1820 China contributes 288 million people to the global poverty count, followed by Japan (29.4), Korea (9.2) and Mongolia (0.6). At the local high of the poverty in 1995, China contributes 815.8 million people in global poverty

<sup>31</sup>Given the special subsection on China below, in this subsection the focus will be mostly on other countries when possible.

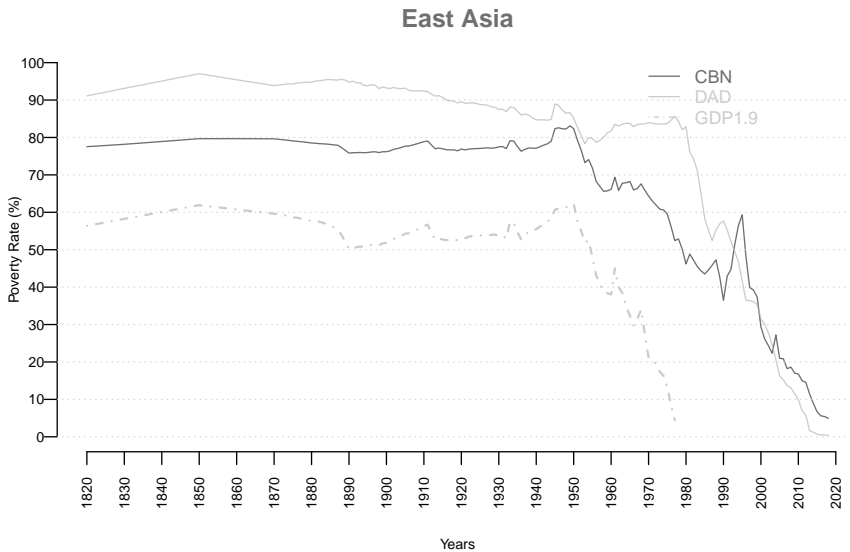


Figure 6.8: Poverty rate for people living in conditions of absolute poverty globally defined for the region of East Asia, in comparison with other estimates.

counts, followed by Mongolia (1.4).<sup>32</sup> In 2018 China contributes 77.1 million people, followed by Japan (1.4), Mongolia (0.5), and Korea (0.3).

Figure 6.9 shows the development of absolute poverty throughout the Middle East and North Africa region. For the best part of the period until 1970, both the DAD and CBN series are close or very close. Absolute poverty fell in the 19<sup>th</sup> century, from 75% in 1820 to 59% by 1900. The pace of reduction is slightly stronger in the first half of the 20<sup>th</sup> century, to 18% by 1974. A sharp decrease follows in the 1980s, bringing poverty to 7% in 1990, and to 1% in 2018.<sup>33</sup>

In terms of the countries' contributions to the total population in absolute poverty, Turkey is the largest contributor in 1820 with approximately 9.1 million, followed by Sudan (5.2), Iran (4.5), and Algeria (1.2). By 1974, Turkey contributes 10.2 million, Sudan (10), Morocco (5.4), and Algeria (1.6). In 2018, Turkey is again the largest contributor, but at considerably lower levels, with 1.7 million people, followed by Yemen (0.8),<sup>34</sup> Sudan (0.3), and Algeria (0.1).

<sup>32</sup>Japan contributes only a few thousand this year, and Korea none.

<sup>33</sup>However, some relatively large countries are missing from this area: Libya, Iraq, and Saudi Arabia. For the first two one would expect very high poverty rates.

<sup>34</sup>This estimate is of particular concern as the data seem not to be representative of the dire

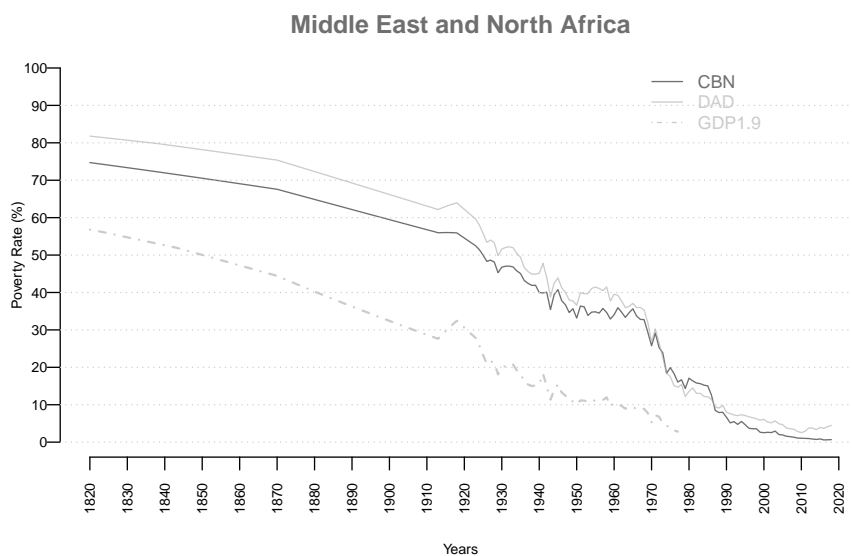


Figure 6.9: Poverty rate for people living in conditions of absolute poverty globally defined for the region of Middle East and North Africa, in comparison with other estimates.

In terms of the contributions of countries to the total population in absolute poverty from this region, in 1820 Turkey is the biggest contributor with approximately 9.1 million, followed by Sudan (5.2), Iran (4.5), and Algeria (1.2). By 1974, Turkey contributes 10.2 million, Sudan (10), Morocco (5.4), and Algeria (1.6). In 2018, Turkey is again the largest contributor with 1.7 million people in absolute poverty, followed by Yemen (0.8)<sup>35</sup>, Sudan (0.3), and Algeria (0.1).

Figure 6.10 shows the evolution of absolute poverty in the Western Offshoots region. This figure, along with table 6.2, show that the Western Offshoots region, which spans across continents, has the lowest poverty rates overall. In a way Western Offshoots are a unique case as they are among the richest countries, yet their absolute poverty lines for most of the period are below or at the DAD poverty line. From the beginning of the period in 1820 Western Offshoots have the lowest poverty rate among all others at 55%. A downward trend is interrupted by 1853, and poverty reduction continues only after 1870. This backstop period surrounds the years of the civil war in USA (1861-1865). The poverty reduction that started after 1870 roughly lasts until 1918 when the regional poverty rate stands at 2%. In the years that follow it is worth noting that the 1929 financial crisis does not show as a spike on a regional level by neither CBN, DAD or GDP1.9, at least not until a few years later when a peak in 1933 at 8% demonstrates a quadruple increase since 1918, and more than double the poverty rates of 1924.

Figure 6.10 shows the evolution of absolute poverty in the Western Offshoots region. This region has the lowest poverty rates throughout the period. Starting from a level of 55% in 1820, the decline in poverty rate come to a halt in 1853, and resumes after 1870 until 1918, when it stands at 2%. Following the 1929 financial crisis, absolute poverty reaches a peak of 8% in 1933, more than double its level in 1924. During WWII, Western Offshoots show no sign of poverty increase, and its rate in 1944 is the world's lowest at 1%. In the years that follow, poverty rates are less than 0.5% and until 1979. The period ends with a rise in absolute poverty to a rate above 1% after 2000. In terms of absolute contributions to global poverty, United States contribute 5.2 million in 1820, followed by Canada (0.6), and Australia (0.3). By 2018, and despite the large reduction in poverty rates, the contributions are almost the identical to those of 1820, with United States contributing 4.9 million, followed by Canada (0.5), and Australia (0.4).

Figure 6.11 shows the evolution of absolute poverty for Sub-Saharan Africa. This region featured the highest poverty rates throughout the entire period, with only very few exceptions. In 1820, the regional poverty rate is 91%, which is still lower than the period's highest of 98% in 1847. Substantial poverty reduction

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situation for the Yemen population due to the ongoing war in its territory.

<sup>35</sup>This estimate is of particular concern as the data seem not to be representative of the dire situation for the Yemen population due to the ongoing war in its territory.

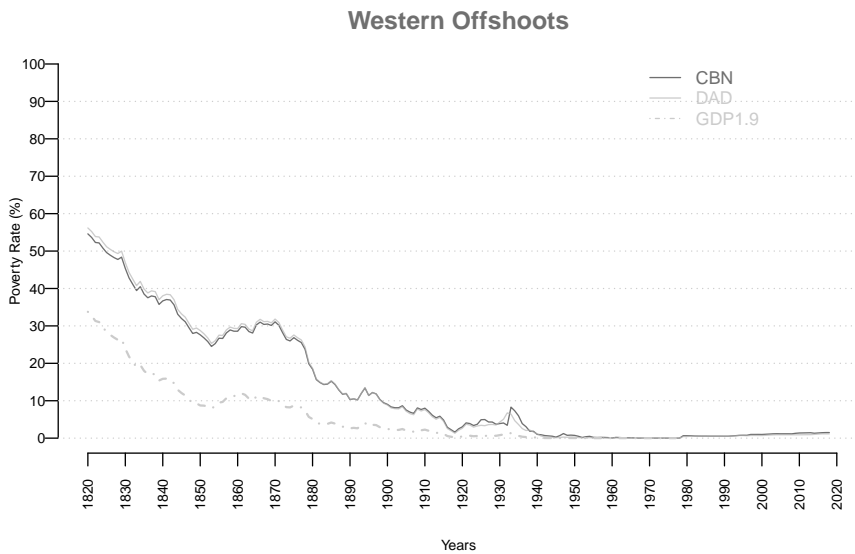


Figure 6.10: Poverty rate for people living in conditions of absolute poverty globally defined for the region of Western Offshoots, in comparison with other estimates.

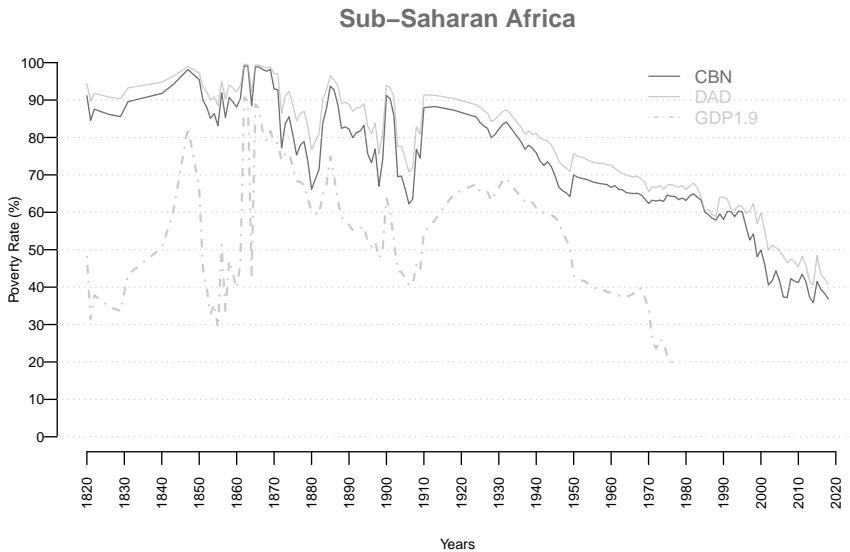


Figure 6.11: Poverty rate for people living in conditions of absolute poverty globally defined for the region of Sub-Saharan Africa, in comparison with other estimates.

starts only after 1917, and brings absolute poverty to a local minimum of 64% by 1949.<sup>36</sup> A slow improvement lasts until 1970, followed by slow increases until 1982. In the later 1980s poverty rates fluctuate around 60% up until 1995 where a strong reduction is observed, bringing poverty rates to around 40%. By 2018 poverty rate, at 37%, is close to its minimum reached in 2014).<sup>37</sup>

In terms of countries' contributions to the total count of absolute poverty, Ethiopia is the biggest contributor in 1820 with approximately 2.9 million, followed by Mozambique (1.9), and Madagascar (1.6).<sup>38</sup> By 1950, when data for

<sup>36</sup>Not many countries from this region have population data prior to 1950 in the sources used here (available pre-1950 population data cover: Angola, Ethiopia, Ghana, Madagascar, Mozambique, Mauritius, Somalia, Sudan, and South Africa). Information from other sources can be added in later implementations to improve coverage.

<sup>37</sup>For Sub-Saharan region in particular there is one additional methodological consideration in terms of comparability with most other regions. The PovcalNet distributions do not use equivalence scales when converting the per household income/consumption to per individual. This way larger families, disproportionately present in the region, are relatively penalized showing a much lower per individual income than when equivalence scales are used (as done by the OECD for example).

<sup>38</sup>Do note that several countries in the region, including Nigeria, are not covered in this year by



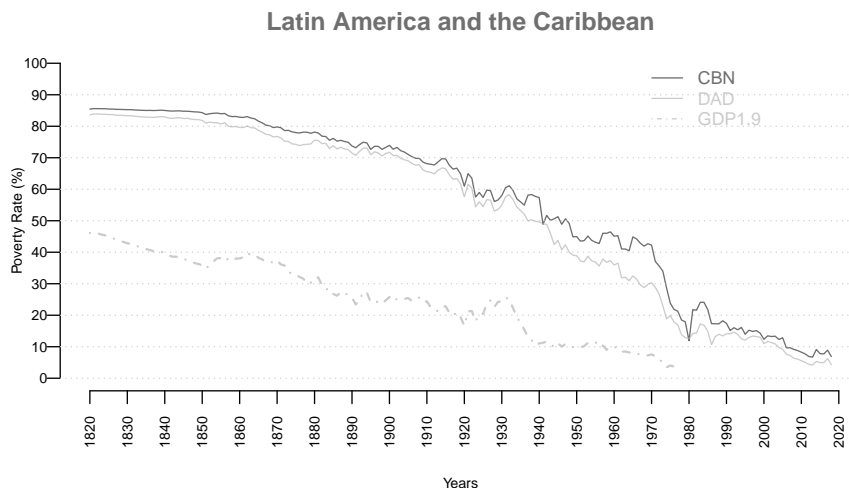


Figure 6.12: Poverty rate for people living in conditions of absolute poverty globally defined for the region of Latin America and the Caribbean, in comparison with other estimates.

many more countries are available, Nigeria contributes 57 million, followed by Ethiopia (22.3), South Africa (7.7) and Kenya (9.2). In 2018, Nigeria is again the largest contributor, with 121.3 million people in absolute poverty, followed by Ethiopia (40.9), Kenya (31.2), Madagascar (14.1) and South Africa (12.3).

Figure 6.12 shows the development of absolute poverty for Latin America and the Caribbean. Starting from a level of 85% in 1820, the poverty rate fell to 45% in 1950, and to 7% by 2018. A strong decline from 42% in 1970 to 12% in 1980, was partially reversed in the following year, doubled the rate to 24% by 1984. Since then, a slow reduction brought absolute poverty to a minimum by 2018. In terms of countries' to the total population in absolute poverty, Mexico is the biggest contributor in 1820, with 5.7 million, followed by Brazil (4.1), Peru (1.2) and Colombia (1.1). By 1950, Brazil contributes 38.4 million, followed by Mexico (10.7), Colombia (4.8) and Peru (4.2). In 2018, Brazil is again the largest contributor with 15.6 million people in absolute poverty, followed by Haiti (7.9), Venezuela (6.7), Peru (3.4), Mexico (2) and Colombia (2.4).

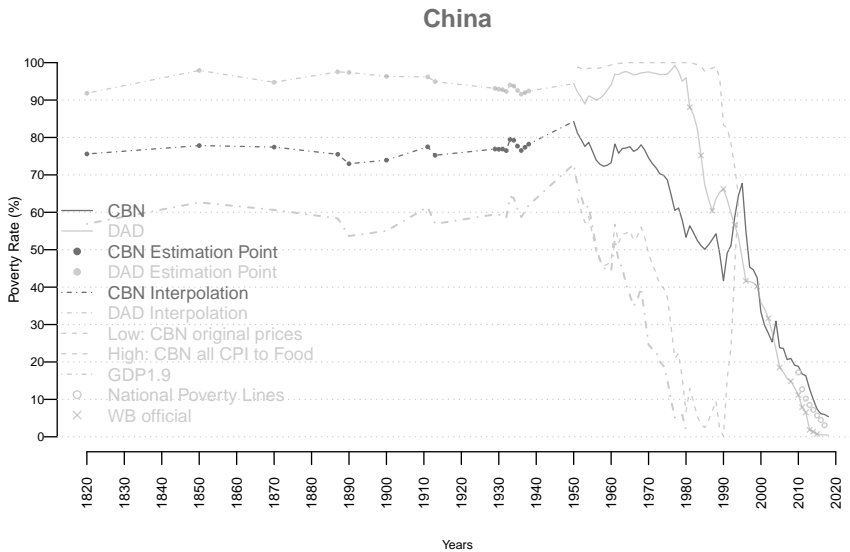


Figure 6.13: Global Poverty rate for people living in conditions of absolute poverty globally defined in China; multiple approaches are shown, and in comparison with other estimates, including the official WB estimates directly from PovcalNet.

## China

China requires special attention for two reasons: it was for a long period a non-market economy, and (because of its size) it has a disproportionate impact on global poverty counts. These two factors imply that uncertainty in Chinese estimates has large implications on a global scale. Figure 6.13 illustrates the magnitude of these concerns. The dark gray line shows the trajectory of poverty rates based on the estimates discussed above, which result from averaging estimates based on two approaches: (a) taking price data at face value for the period 1990-1995; and (b) attributing all CPI change to non-food items (explanation follows). Scenario (a) is based on the same approach used for all other estimates presented in this chapter, i.e. using nominal prices to estimate the CPF food poverty line, and then applying to them multipliers to obtain the Basic Diet and the non-Food poverty lines. The only difference is that the nominal prices used here are not those from the ILO data but from the Chinese Statistical Yearbooks.<sup>39</sup> This estimate (the dashed light

<sup>39</sup>This is done as a robustness check but the same results obtain with ILO data as well. The advantage in keeping the Yearbook statistics is that they reduce the reliance to CPI conversions as

gray line at the bottom of Figure 6.13) shows almost zero absolute poverty rate in 1990, which is unrealistic. The alternative approach is based on the idea that, since food prices have a much higher volatility in this period than the CPI, all CPI change reflect changes in the food component of the index, and that prices for the non-food items of the poverty basket over the period 1990-1994 are at the level attained in 1995. This alternative estimate (shown by the dashed light gray line at the top of Figure 6.13) is close to 100% in 1990.

## 6.6. Correlation with GDP per capita

Figure 6.14 shows the correlation between the CBN-based poverty rates and the estimates for GDP per capita shown in Chapter 2 in each year. Across the full period, the correlation is  $-0.59$ , implying that countries with higher GDP per capita also feature lower rates of absolute poverty, with the largest value, of about  $-0.77$  achieved in 1919, and the smallest one in 1831 at  $-0.3$ . In the post-World War II period, the largest correlation of about  $-0.63$  is achieved in 1978, and the smallest at  $-0.48$  in 2014. The decline in this correlation may be explained by the increase of the within-countries inequality observed in the period between those years, albeit at different rates between countries.

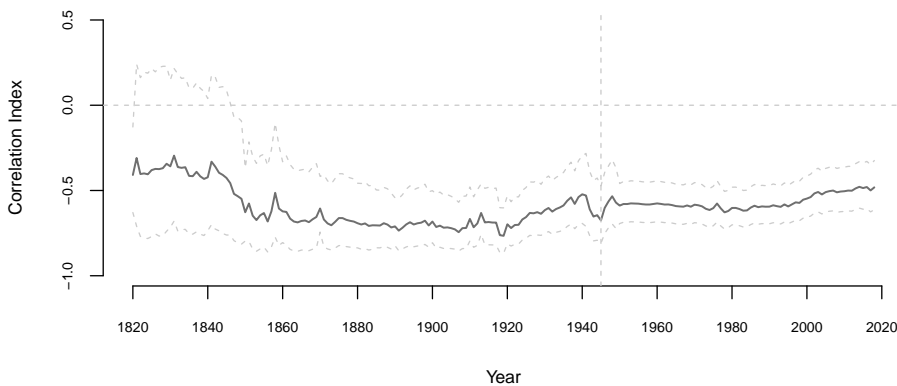


Figure 6.14: Correlation with GDP per capita, along with a 95% confidence interval.

At the same time, the drop in global poverty after 1995 is the largest observed, they offer complete coverage of basic items, and cover up to, and including, 2014.

despite the low correlation with GDP per capita. This implies a 'lost opportunity', for even faster poverty reduction could have been achieved if measures had been taken to contain increasing within-countries inequality. It should be noted though, that the confidence intervals around these correlation coefficients are very high, implying that other factors beyond GDP per capita played a role. The confidence interval around the correlation coefficient stretches into positive terrain in the early 19<sup>th</sup> century, implying that in the early 19<sup>th</sup> century some countries with high absolute poverty featured high GDP per capita and vice-versa.

## 6.7. Priorities for Future Research

This first attempt to estimate global absolute poverty using a cost of basic needs approach over the long run highlights a number of novel empirical patterns but also the many areas where more historical research is needed. In particular, the global character of our exercise, and the still sparse availability of relevant data, has required taking shortcuts on a number of empirical issues. Most importantly, to account for a richer diet and for other non-food costs, our estimates rely on Allen's 'multipliers' for 2011, instead of a direct calculation. Moving beyond this assumption will require the assembly of a broader global dataset on prices of all products and services relevant to those living in poverty. Such a dataset could then be used to provide direct estimates of poverty lines covering housing, education, health care and heating. Such a broader set of data on the prices of different consumption items would allow overcoming another limit of the estimates presented in this chapter, i.e. the extensive use of CPI information.

An additional important consideration is the fixity across time of the welfare standard used here. The poverty line favoured by Allen (2017) and used in this chapter is based on a requirement of 2100 kcal of energy per person per day. Conversely, FAO (2001, 2008) provide measures of the –so called– minimum dietary energy requirement as a function of the population's age and gender. Applying the approach used in this chapter to these minimal dietary energy requirements would allow providing estimates of absolute poverty that take into account changes in population structure over long periods of time. The same approach could be applied to take into account the Physical Activity Level of those living in poverty (i.e. the physical intensity of work, home, leisure and life conditions), which plays an important role in shaping the nutrient targets which needs to be considered.

At the same time, secondary indicators are needed to address the problem of prices unrepresentativeness in non-market economies, in particular for China and the former Soviet Union. Moreover, a priority for future historical research should be to produce metrics of the sensitivity of the poverty rate with respect to the

poverty line.<sup>40</sup>

Finally, and on a more conceptual level, the relative poverty component is entirely ignored here, and more generally in the global poverty measurement empirical literature, with two notable exceptions: Atkinson and Bourguignon (2001) and Ravallion and Chen (2011), both however rely on the PPP equivalence. A more complete approach to global poverty measurement requires to also consider relative poverty issues, possibly by expanding these contributions to the cost of basic needs domain. This is best explained by Sen (1983), who convincingly postulates that for a poverty line to be kept fixed in absolute terms within the space of welfare would require this poverty line to encapsulate a relative component in the space of incomes (or consumption). Any estimation of global poverty will remain incomplete if this conceptual issue is not adequately addressed.

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<sup>40</sup>One can consider using the 84th or 97.5th percentile of a poverty line estimated with Monte Carlo simulations for instance. See Moatsos and Lazopoulos (2019) and Moatsos (2017b) for such simulations. Alternatively, fuzzy approaches in estimating poverty rates may provide a promising solution (Betti et al., 2006).



## **Chapter 7**

# **Appendix**

### **7.1. Comparative Global, Regional and Populous Country Poverty Tables**







Table 7.3: Comparison of Poverty Rate Estimates for: South Asia, SA

Study	1820	1870	1910	1950	1960	1970	1975	1981	1984	1987	1990	1993	1996	1999	2002	2005	2015
	<i>\$1.02/day@1985PPP</i>																
Ravallion et al. (1991a), D	-	-	-	-	-	-	-	-	50.9 <sup>1985</sup>	-	-	-	-	-	-	-	-
95% CI	-	-	-	-	-	-	-	-	49.8~52.6 <sup>1985</sup>	-	-	-	-	-	-	-	-
Chen et al. (1994), D	-	-	-	-	-	-	-	-	60.84 <sup>1985</sup>	-	58.60	-	-	-	-	-	-
Ravallion and Chen (1997), D	-	-	-	-	-	-	45.4	43.0	43.1	-	-	-	-	-	-	-	-
	<i>\$1.08/day@1993PPP</i>																
Chen and Ravallion (2001), D	-	-	-	-	-	-	-	-	-	44.94	44.01	43.39	42.26	40.00 <sup>1998</sup>	-	-	-
Chen and Ravallion (2004), D	-	-	-	-	-	-	-	51.5	46.8	45.0	41.3	40.1	36.6	32.2	31.1 <sup>2001</sup>	-	-
	<i>\$1.25/day@2005PPP</i>																
Chen and Ravallion (2010), D	-	-	-	-	-	-	-	41.9	38.0	36.6	34.0	29.3	29.1	26.9	26.5	23.7	-
Ferreira et al. (2016), D	-	-	-	-	-	-	-	-	-	-	54.1	-	-	45	-	-	24.5 <sup>2011</sup>
	<i>\$1.52&amp;\$3.04/day@2000PPP, Income/NAS Based</i>																
Pinkovskiy and Sala-i Martin (2009)	-	-	-	-	-	20.1	19.0	11.1	8.5	5.7	4.3	4.6	4.9	3.3	3.3	2.9	-
(ibid)	-	-	-	-	-	58.7	57.3	46.6	41.5	34.2	28.8	28.3	25.2	17.0	14.4	11.2	-
	<i>\$1.9/day@2011PPP, Consumption/Income/Survey Based</i>																
Ferreira et al. (2016), D	-	-	-	-	-	-	-	-	-	-	50.6	-	-	-	-	-	18.8 <sup>2012</sup>
PovcalNet (Jan 6, 2020)	-	-	-	-	-	-	-	55.7	53	50	47.3	44.9	40.3	-	38.6	33.7	16.2 <sup>2013</sup>
Chapter 6 from this thesis, CBN <sup>1</sup>	68.7	73.8	57.9	66.8	68.9	64.3	61.4	48	49	50.4	47.5	46.1	39.8	38.2	31.4	26.3	14.2
Chapter 6 from this thesis, \$1.9/day <sup>1</sup>	68.2	73.2	56.5	66.6	71	64.5	62.8	55.7	51.6	49	45.6	43.6	38.1	36.6	33.3	28.6	11.6
	1820	1870	1910	1950	1960	1970	1975	1980	1985	1990	1995	2000	2005	2015			
	<i>\$1.5&amp;\$2/day@1993PPP, Income/NAS Based</i>																
Bhalla (2002a), D	-	-	-	44.3	37.2	32.1	-	34.4	-	18.5	-	-	-	7.8	-	-	-
(ibid), D	-	-	-	64.3	58.1	55.2	-	56.3	-	39.3	-	-	-	21.1	-	-	-
	<i>\$1.50/day@1996PPP</i>																
Sala-i Martin (2006)	-	-	-	-	-	30.3	29.7	26.7	17.8	10.3	5.7	-	-	2.5	-	-	-
	<i>\$1.52&amp;\$3.04/day@2000PPP, Income/NAS Based</i>																
Pinkovskiy and Sala-i Martin (2009)	-	-	-	-	-	20.1	19.0	12.2	7.1	4.3	5.1	4.3	3.7	3.7	2.9	2.9	-
(ibid)	-	-	-	-	-	58.7	57.3	48.5	38.6	28.8	26.7	16.5	16.5	11.2	11.2	-	-

D stands for developing world only, otherwise the intended coverage is global; 1. South and South-East Asia.





Table 7.6: Comparison of Poverty Rate Estimates for: Middle East and North Africa, MENA

Study	1820	1870	1910	1950	1960	1970	1975	1981	1984	1987	1990	1993	1996	1999	2002	2005	2015
<i>\$1.02/day@1985PPP</i>																	
Ravallion et al. (1991a), D	-	-	-	-	-	-	-	-	31 <sup>1985</sup>	-	-	-	-	-	-	-	-
95% CI	-	-	-	-	-	-	-	-	13.3~50.9 <sup>1985</sup>	-	-	-	-	-	-	-	-
Chen et al. (1994), D	-	-	-	-	-	-	-	-	4.49 <sup>1985</sup>	-	2.52	-	-	-	-	-	-
Ravallion and Chen (1997), D	-	-	-	-	-	-	-	-	-	4.7	4.3	4.1	-	-	-	-	-
<i>\$1.08/day@1993PPP</i>																	
Chen and Ravallion (2001), D	-	-	-	-	-	-	-	-	-	4.30	2.39	1.93	1.83	2.11 <sup>1998</sup>	-	-	-
Chen and Ravallion (2004), D	-	-	-	-	-	-	-	5.1	3.8	3.2	2.3	1.6	2.0	2.6	2.4 <sup>2001</sup>	-	-
<i>\$1.25/day@2005PPP</i>																	
Chen and Ravallion (2010), D	-	-	-	-	-	-	-	3.3	2.4	2.3	1.7	1.5	1.6	1.7	1.4	1.6	-
Ferreira et al. (2016), D	-	-	-	-	-	-	-	-	-	-	5.8	-	-	4.8	-	-	1.7 <sup>2011</sup>
<i>\$1.52&amp;\$3.04/day@2000PPP, Income/NAS Based</i>																	
Pinkovskiy and Sala-i Martin (2009)	-	-	-	-	-	8.4	7.0	4.3	2.2	2.3	4.0	4.1	2.4	1.4	1.1	5.2	-
(ibid)	-	-	-	-	-	25.3	23.2	17.4	12.1	11.6	14.3	14.1	11.9	10.7	9.4	12.9	-
<i>\$1.9/day@2011PPP, Consumption/Income/Survey Based</i>																	
Ferreira et al. (2016), D	-	-	-	-	-	-	-	-	-	-	6	-	-	4.2	-	-	-
PovcalNet (Jan 6, 2020)	-	-	-	-	-	-	-	-	8.9	8.1	6.2	7	6.2	3.8	3.4	3	4.2
Chapter 6 from this thesis, CBN	78.7	72.4	62.6	39.6	40.8	32.9	27.5	24.5	23.7	8.5	6.7	4.7	3.7	2.6	2.6	1.9	0.9
Chapter 6 from this thesis, \$1.9/day	80	73.6	61.4	35.6	38.5	27.3	17.2	14.5	12.2	9.5	8	7.1	6.8	5.9	5.2	4.7	3.9
<i>\$1.5&amp;\$2/day@1993PPP, Income/NAS Based</i>																	
Bhalla (2002a), D	-	-	-	26.3	24.3	13.4	-	4.3	-	-	5.2	-	-	-	7.8	-	-
(ibid), D	-	-	-	40.3	37.2	23.3	-	10.4	-	-	10.2	-	-	-	14.0	-	-
<i>\$1.50/day@1996PPP</i>																	
Sala-i Martin (2006)	-	-	-	-	-	10.7	9.2	3.6	1.6	-	1.2	0.7	-	0.6	-	-	-
<i>\$1.52&amp;\$3.04/day@2000PPP, Income/NAS Based</i>																	
Pinkovskiy and Sala-i Martin (2009)	-	-	-	-	-	8.4	7.0	4.2	2.1	-	4.0	3.3	-	1.3	3.8	-	-
(ibid)	-	-	-	-	-	25.3	23.2	16.0	11.9	-	14.3	13.4	-	10.2	12.9	-	-
<i>\$1&amp;\$2/day@2005PPP, Income/NAS Based</i>																	
Zanden van et al. (2011)	30.4	28.6	20.4	8.1	8.2	4.3	2.0	-	-	-	2.5	-	-	1.8	-	-	-
(ibid)	62.6	56.2	44.7	28.3	26.7	16.9	-	9.0	-	-	10.5	-	-	7.3	-	-	-

D stands for developing world only, otherwise the intended coverage is global.

Table 7.7: Comparison of Poverty Rate Estimates for: Latin America and the Caribbean, LAC

Study	1820	1870	1910	1950	1960	1970	1975	1981	1984	1987	1990	1993	1996	1999	2002	2005	2015
	<i>\$1.02/day@1985PPP</i>																
Ravallion et al. (1991a), D	-	-	-	-	-	-	-	-	19.1 <sup>1985</sup>	-	-	-	-	-	-	-	-
95% CI	-	-	-	-	-	-	-	-	14.0~28.9 <sup>1985</sup>	-	-	-	-	-	-	-	-
Chen et al. (1994) <sup>1</sup> , D	-	-	-	-	-	-	-	-	23.07 <sup>1985</sup>	-	27.77	-	-	-	-	-	-
Ravallion and Chen (1997), D	-	-	-	-	-	-	-	-	-	22.0	23.0	23.5	-	-	-	-	-
	<i>\$1.08/day@1993PPP</i>																
Chen and Ravallion (2001), D	-	-	-	-	-	-	-	-	-	15.33	16.80	15.31	15.63	12.13 <sup>1998</sup>	-	-	-
Chen and Ravallion (2004), D	-	-	-	-	-	-	-	9.7	11.8	10.9	11.3	11.3	10.7	10.5	9.5 <sup>2001</sup>	-	-
	<i>\$1.25/day@2005PPP</i>																
Chen and Ravallion (2010), D	-	-	-	-	-	-	-	7.7	9.2	8.9	6.6	6.0	7.3	7.4	7.7	5.6	-
Ferreira et al. (2016), D	-	-	-	-	-	-	-	-	-	-	12.6	-	-	11	-	-	4.6 <sup>2011</sup>
	<i>\$1.52&amp;\$3.04/day@2000PPP, Income/NAS Based</i>																
Pinkovskiy and Sala-i Martin (2009)	-	-	-	-	-	11.6	6.2	4.2	4.8	4.5	5.2	5.1	4.9	4.8	4.7	3.3	-
(ibid)	-	-	-	-	-	25.6	17.0	12.8	14.2	13.5	14.9	14.6	14.2	13.9	13.7	10.7	-
	<i>\$1.9/day@2011PPP, Consumption/Income/Survey Based</i>																
Ferreira et al. (2016), D	-	-	-	-	-	-	-	-	-	-	17.8	-	-	13.9	-	-	5.6 <sup>2012</sup>
PovcalNet (Jan 6, 2020)	-	-	-	-	-	-	-	13.5	16.5	13.5	14.9	14	13.7	13.5	11.8	9.9	3.9
Chapter 6 from this thesis, CBN	85.4	79.8	68.1	45	45.2	42.3	23.9	21.8	24.2	17.4	17.5	15.5	15.2	14.3	13.2	12.9	7.8
Chapter 6 from this thesis, \$1.9/day	83.6	76.8	65.6	38.9	35.9	30.3	19.9	14.1	16.8	13.2	14.1	13.9	12.9	13	11.3	9.2	5
	1820	1870	1910	1950	1960	1970	1975	1980	1985	1990	1995	2000	2005	2015			
	<i>\$1.5&amp;\$2/day@1993PPP, Income/NAS Based</i>																
Bhalla (2002a), D	-	-	-	22.0	16.0	9.4	-	3.6	-	5.3	-	-	-	5.2	-	-	-
(ibid), D	-	-	-	31.3	24.5	15.4	-	8.2	-	10.8	-	-	-	10.4	-	-	-
	<i>\$1.50/day@1996PPP</i>																
Sala-i Martin (2006)	-	-	-	-	-	10.3	5.6	3.0	3.6	4.1	3.8	-	-	4.2	-	-	-
	<i>\$1.52&amp;\$3.04/day@2000PPP, Income/NAS Based</i>																
Pinkovskiy and Sala-i Martin (2009)	-	-	-	-	-	11.6	6.2	4.0	4.8	5.2	4.9	-	-	4.5	3.3	-	-
(ibid)	-	-	-	-	-	25.6	17.0	12.6	14.1	14.9	14.3	-	-	13.2	10.7	-	-
	<i>\$1&amp;\$2/day@2005PPP, Income/NAS Based</i>																
Zanden van et al. (2011)	32.9	22.9	5.5	2.6	4.8	3.0	-	1.0	-	1.4	-	-	-	1.4	-	-	-
(ibid)	56.3	48.7	20.5	11.5	13.7	9.7	-	4.3	-	5.3	-	-	-	4.7	-	-	-

D stands for developing world only, otherwise the intended coverage is global.



## 7.2. Appendix for Global Absolute Poverty, Present and Past since 1820

### 7.2.1 Calculations and Imputations on Country Level

The cost of a consumption basket that provides for (at least<sup>1</sup>) 2100 kcal, 40 gr of proteins, and 34 gr of fat (CPF basket), is being multiplied by the average increase in the cost of the CPF basket to a Basic Diet basket; this factor is around 1.8 (see below). Then depending on the real gdp per capita another parameter obtains which corresponds to the share of the food component in the final poverty line. This can be from 70 down to 20 percent. This parameter acts essentially as another multiplier, which then gives the final cost of the poverty line. Once there are no more data to estimate the cost of the poverty line, I am using the most appropriate from the available CPI indexes to impute its food cost, and then apply the aforementioned multipliers.<sup>2</sup> If no CPI data are available, I am using the PPP assumption (meaning I keep the food component fixed in PPP dollars) while applying the aforementioned multipliers—which vary per year according to the GDP per capita of the country—upon that fixed value.

For distributional data, I start from the World Bank's PovcalNet data. These data provide two very important features: 1) return a poverty rate based on the actual distribution (no lognormality assumption is needed), and 2) the mean value of the household survey is also available (a variable which is not available for the historical income distribution data). Therefore the mean value from those surveys is used for other years as well, shifted by the real growth of the household consumption from the national account statistics (useful for post 1950 years, and for 20 countries covered by the MacroHist database for post 1870 years), or from the its relation as a share of real gdp per capita (for years where NAS household consumption data are not available). Any other source of inequality information in terms of Gini is also utilized with a selection process for the underlying properties of each datapoint (see the main text for details).

This way I have a poverty line in 2011 PPP dollars, a distribution and the distribution's mean for each year that this is possible. In the event that some or all

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<sup>1</sup>"at least" in the sense that it may well be that the cheapest way to achieve those nutrients would be one with say 2100 kcal, 67 gr of proteins and 34 gr of fat.

<sup>2</sup>In order of preference: World Bank WDI data, Jordà et al. (2016) CPI data, IMF CPI data, Clio Infra Consumer Price Index dataset from the Clio Infra project website (dataset downloaded from <https://clio-infra.eu/Indicators/Inflation.html> on 12, August 2015), Balkans CPI (historical CPI series from Balkan countries: South-Eastern European Monetary and Economic Statistics from the Nineteenth Century to World War II, published by: Bank of Greece, Bulgarian National Bank, National Bank of Romania, Oesterreichische Nationalbank, 2014, Athens, Sofia, Bucharest, Vienna), ILO general CPI, ILO food CPI, FAOSTAT, and OECD CPI index.



these ingredients are missing I revert to imputation based on information from other countries (which is an improved version of the World Bank method of regional imputation simply by assuming; see Regional Imputation below).<sup>3</sup>

## 7.2.2 Calculations and Imputations on Global and Regional Level

When all data are available for a region (or the world) at a particular year then the calculation is simply the sum of the product of national poverty rate and national population, divided by the total regional (global) population. However, it is very rarely the case that all data from all countries are available (actually it never happens).

### Regional Imputation

For poverty rates outside of those ideal years, I take the last available poverty rate of that country and I “move” it to the first year with non available poverty rate by applying the regional poverty rate growth. This method is applied sequentially until all years are covered. The growth rate of the regional poverty rate is based only on countries with available poverty rates in both years, and excluding poverty rates that come as a result of imputation at a regional level (also excluding estimates based on linear interpolation).

### 7.2.3 Shortcuts over Allen

Figure 7.1 shows the two relationships used in estimating the Basic Diet multiplier and the Food Share in the poverty line. The fitting is done by a simple loess function, with an alpha parameter of 3 controlling the degree of smoothing.<sup>4</sup> On the top of the figure the basic diet multiplier is shown, which has a slow decreasing trend as a function of GDP per capita. The values assigned to this multiplier roughly vary between 2 and 1.6. On the low part of the figure the food share estimation is

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<sup>3</sup>When there are available poverty rates estimates for a country at some discontinuous years then I simply take the linear interpolation of those poverty rates for the years in between. I assume that for those countries this is a better alternative than the regional imputation explained below.

<sup>4</sup>As explained in the chapter France is excluded from the estimation of the multipliers because of a large difference in the price of wheat flour in 2011 between ILO CPI-projected estimate and the 2011 ICP price data. The price for wheat flour used by Allen appears very low relative to the ILO price data used here, at less than 0.5 euro per kg in 2011. The ILO data imply a price of about 1.5 euro for 2011 (last actual price available is 5.32 francs—or 0.81 euro—in 1984. For the other countries which take part in the loess estimation procedure, the country fixed effect makes certain that the same multiplier from the Allen data is applied for the same countries in my dataset. Therefore no divergence is there in terms of different multiplier, and this means that the entire difference is attributable to the differences in prices.

shown, as a function of GDP per capita. Here the typical values are around 70% for low GDP per capita levels and up to about 20% for the highest levels.

#### **7.2.4 Additional remarks on territorial entities (or countries)**

This exercise treats territorial entities as they are currently registered in the various databases used here, taking World Bank and United Nations as a starting point. For those entities the calculations go back to 1820 “as if” they existed back then, although this is not true for a number of cases. In these terms, poverty rate for Italy in 1820 or Lithuania in 1965 should be thought of as the equivalent poverty that would have existed if this entity existed at the time, *ceteris paribus*. In that respect, for countries from the former Soviet Union their GDP per capita estimates (when not directly available from Maddison) were taken from the earliest values available upon which the growth rates from Soviet Union are applied to go back in time (similarly for other countries that were dissolved such as Czechoslovakia or Yugoslavia, when necessary).

#### **7.2.5 Comparison with Allen’s 2017 AER Table 11**

In table 7.10 I compare my results in terms of Basic Diet Poverty Lines with Allen’s 2017 AER Table 11. Some differences in the estimates are evident, as values deviating from 1 in the last column, linked entirely to the different price data used, and on average my estimates of the Basic Diet come rather sufficiently close at 1% of Allen’s estimates. In some countries though this difference is substantial (Algeria, Indonesia, Turkey, Zimbabwe, Bangladesh, Great Britain), and in a couple of cases very large as in Myanmar, Egypt, and Lithuania. However, no obvious errors have been identified in the price series to warrant exclusion, and therefore all these countries are kept in the calculations. The following sub-section includes some excluded countries.

#### **7.2.6 Notes concerning decisions about data exclusion**

From the price data I remove entries for Latvia, Cote d’Ivoire, Azerbaijan, Georgia and Tajikistan due to extremely high values in PPP terms prior to 1990, and prices for Argentina prior to 1966 for the same reason. Similarly prices from Brazil in 1976-1979 were removed again due to extremely high poverty line values in 2011 PPP terms. Also a substantial number of prices were removed from the ILO price dataset prior to linear programming and CPI based price imputation, due to their highly unlikelihood of being non-typos (in any case it is a small share of the total

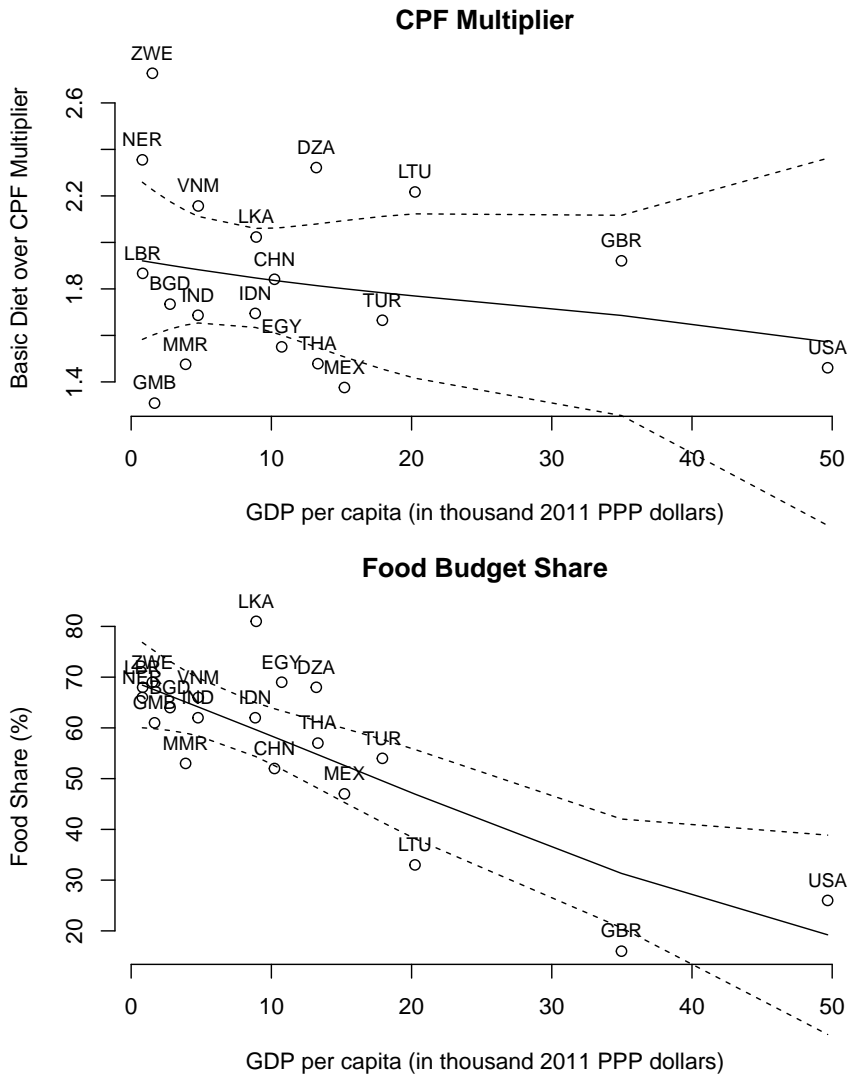


Figure 7.1: This figure shows the two relationships used in estimating the Basic Diet multiplier and the Food Share in the poverty line.

Table 7.10: Comparison with Allen's Table 11 from AER

<b>ISO3</b>	<b>Allen CPF</b>	<b>Allen Basic Diet</b>	<b>Moatsos Basic Diet</b>	<b>RatioOverAllen's</b>
NER	1.154	1.857	1.492	0.80
ZWE	0.984	1.744	1.066	0.61
GMB	1.246	1.455	1.560	1.07
LBR	2.185	3.202	NA	NA
EGY	2.423	3.191	0.848	0.27
DZA	1.853	3.048	1.670	0.55
IND	1.517	2.032	1.838	0.90
CHN	1.825	2.394	2.642	1.10
THA	2.832	3.479	2.775	0.80
IDN	2.426	3.252	2.071	0.64
BGD	1.357	1.866	2.840	1.52
MMR	2.740	3.308	1.194	0.36
LKA	1.441	2.432	2.481	1.02
VNM	2.297	3.546	NA	NA
TUR	1.638	2.089	1.226	0.59
MEX	1.743	2.002	1.582	0.79
LTU	3.769	4.618	1.855	0.40
GBR	3.215	3.491	5.762	1.65
USA	3.424	3.724	3.329	0.89
FRA	3.378	4.017	4.745	1.18

observations, at less than 1%).<sup>5</sup>

## 7.2.7 Tables for all included geographical entities

Table 7.11: Global and Regional poverty rates 1820-2018.

Year	EA	SSEA	EEfSU	LAC	MENA	SSA	WE	WO	World
1820	78	69	91	85	75	91	73	55	76
1830	78	69	86	85	73	88	70	45	75
1840	79	69	87	85	72	92	68	37	75
1850	80	69	84	84	71	95	65	28	74
1860	80	71	72	83	69	88	62	29	72
1870	80	74	68	80	68	93	59	31	71
1880	79	72	56	78	65	66	53	18	67
1890	76	68	52	74	62	82	44	10	62
1900	76	66	43	74	59	91	41	9	60
1910	79	58	39	68	57	88	38	8	56
1920	77	62	63	61	55	87	38	3	59
1930	77	54	37	58	47	82	31	4	53
1940	77	58	26	57	40	76	26	1	51
1950	82	67	19	45	33	70	21	1	53
1955	72	68	13	43	35	68	14	0	49
1960	66	69	8	45	34	67	11	0	48
1965	68	67	5	45	36	65	5	0	47
1970	64	64	2	42	26	62	2	0	45
1975	60	61	2	24	20	65	0	0	42
1980	46	50	3	12	17	63	0	1	34
1985	44	46	2	22	15	60	0	1	33
1990	37	47	1	17	7	58	0	1	31
1995	59	41	15	14	5	60	0	1	36
2000	29	35	13	12	3	50	0	1	25
2005	21	26	5	13	2	42	1	1	20
2010	17	23	3	8	1	41	1	1	17
2015	7	14	2	8	1	42	1	1	12
2018	5	10	2	7	1	37	1	1	10

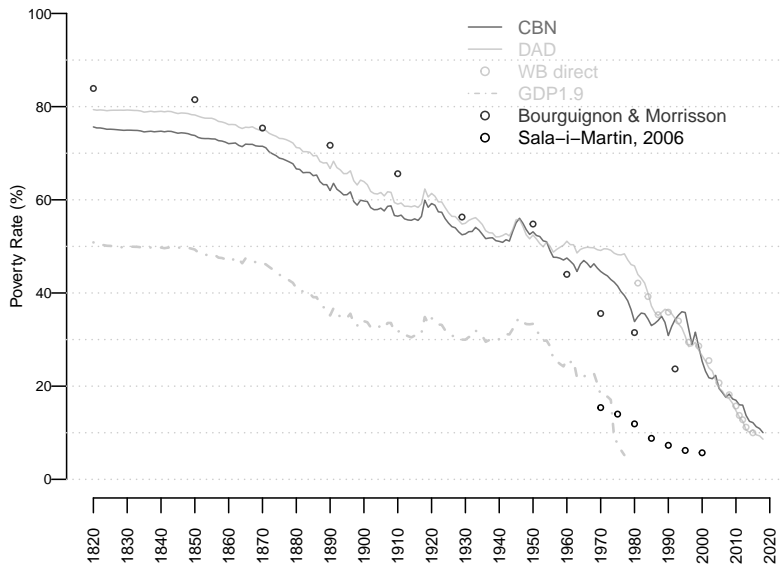
<sup>5</sup>A detailed list will be provided in a working paper explaining the procedure of ILO data assembly and cleaning in detail.

### **7.2.8 Plots for all included geographical entities**

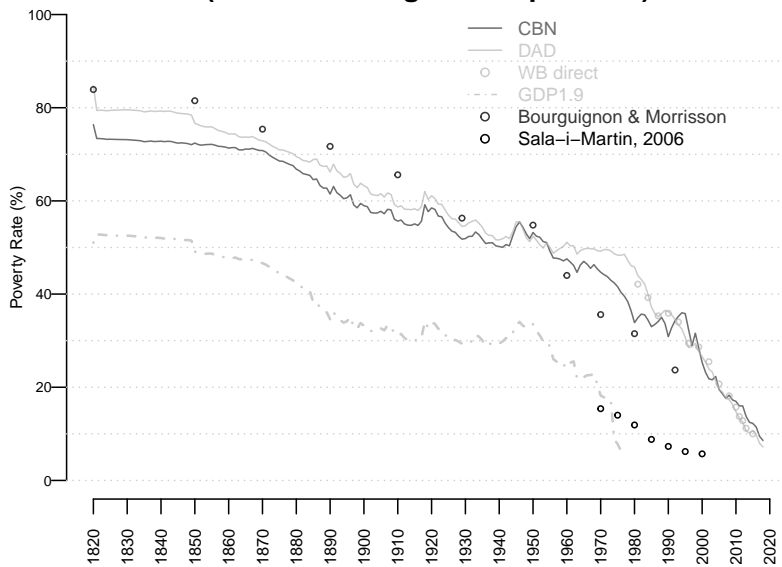
In the following pages figures showing the global and regional aggregates are presented (with and without the aggregation method of regional imputation described above for comparison). Those figures are followed by the plots at the country level, each of which is accompanied with a detailed sub-plot showing the underlying data and imputations. The country plots are grouped first by region and then by population size. For convenience, the first country level plots are the 25 Clio focus countries.

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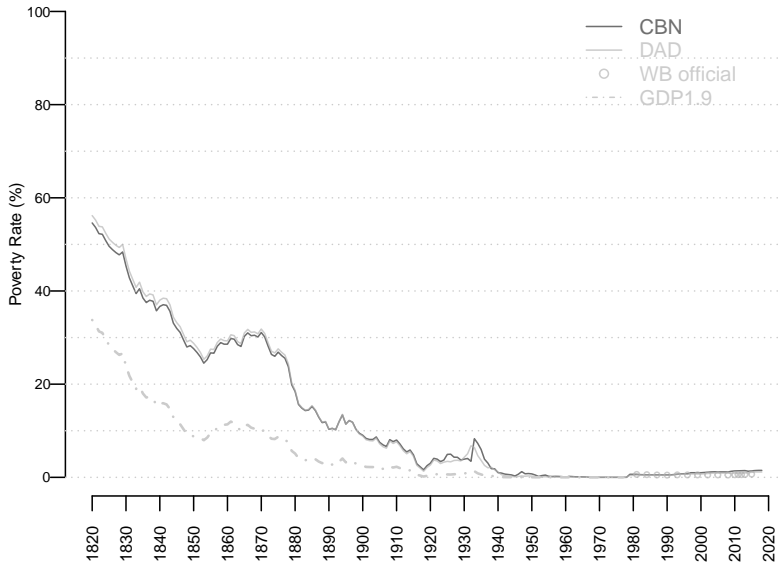
## Poverty Rates in World



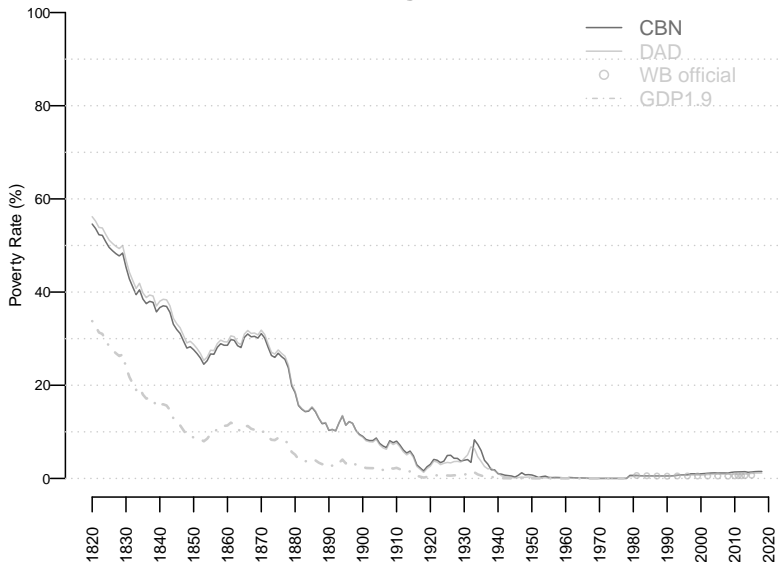
## (without the regional imputation)



### Poverty Rates in W. Offshoots

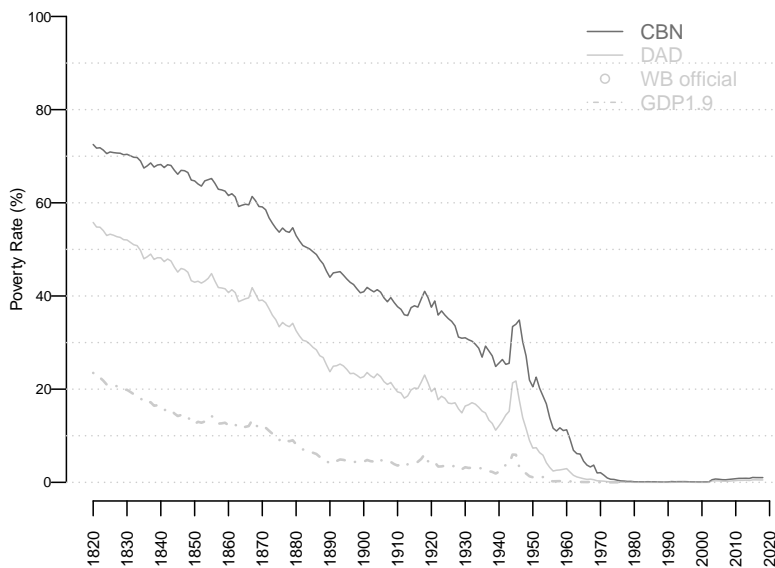


### (without the regional imputation)

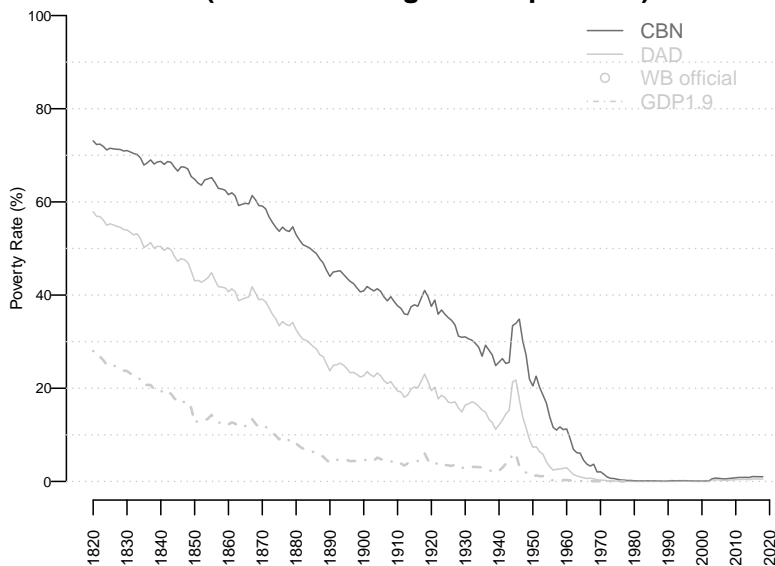




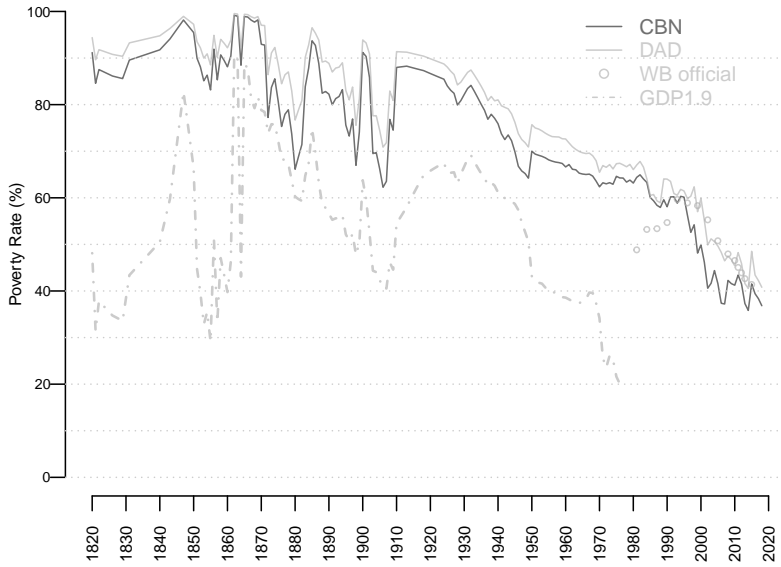
### Poverty Rates in W. Europe



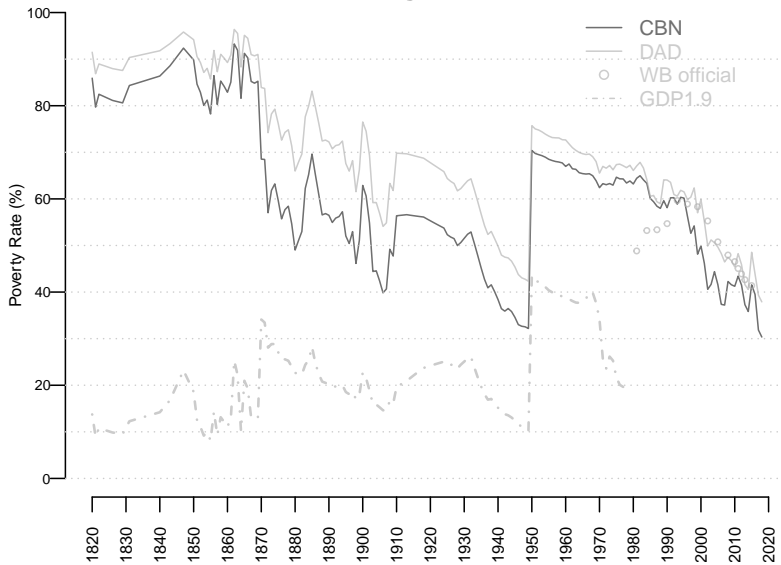
### (without the regional imputation)



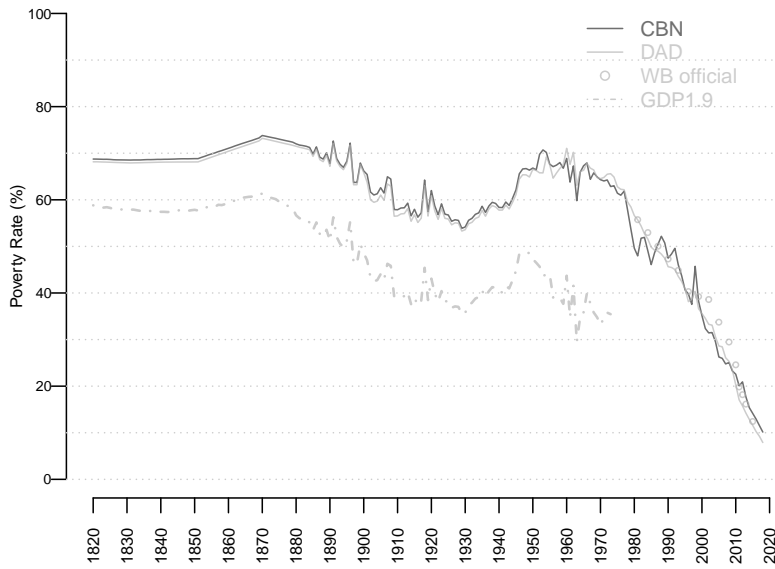
### Poverty Rates in Sub-Saharan Africa



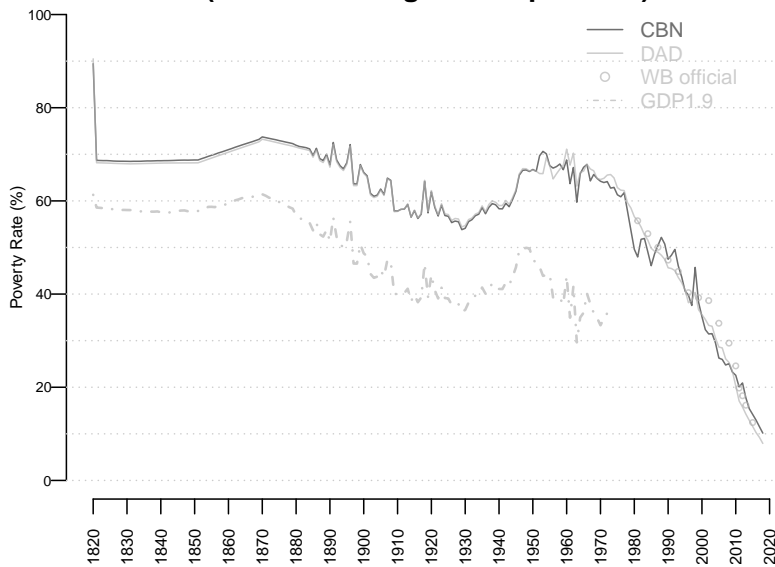
### (without the regional imputation)



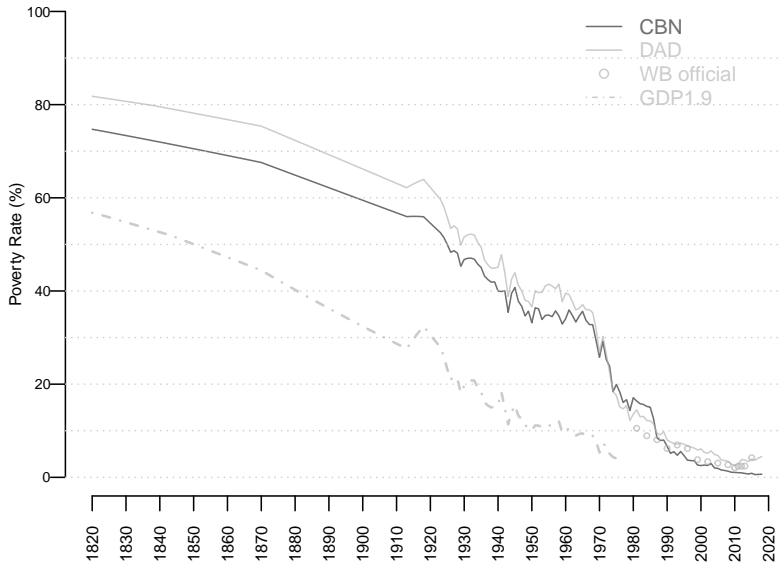
### Poverty Rates in South and South-East Asia



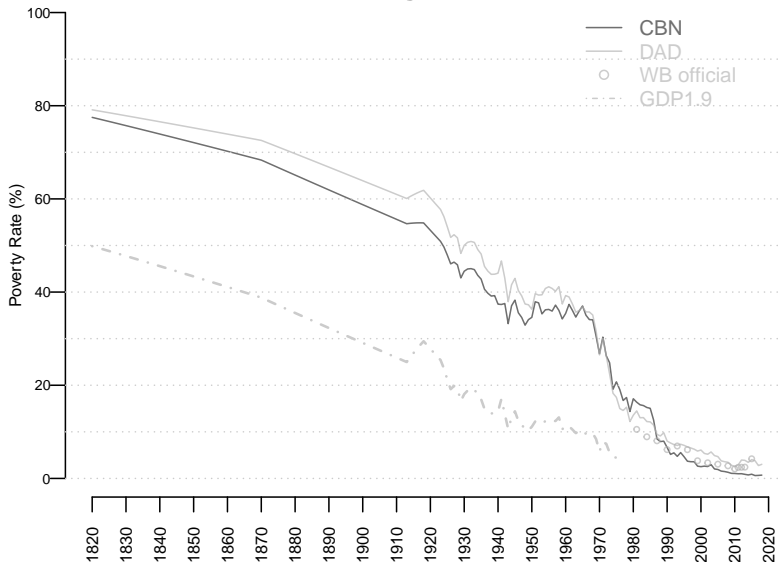
### (without the regional imputation)



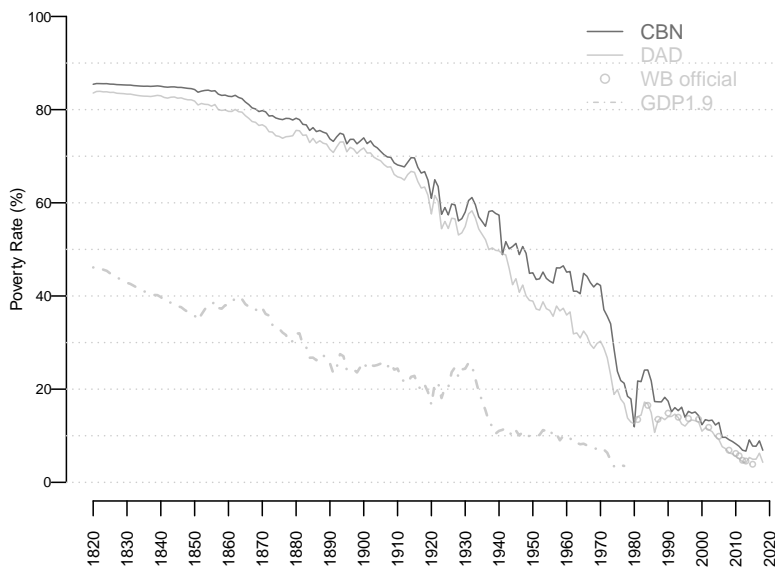
### Poverty Rates in MENA



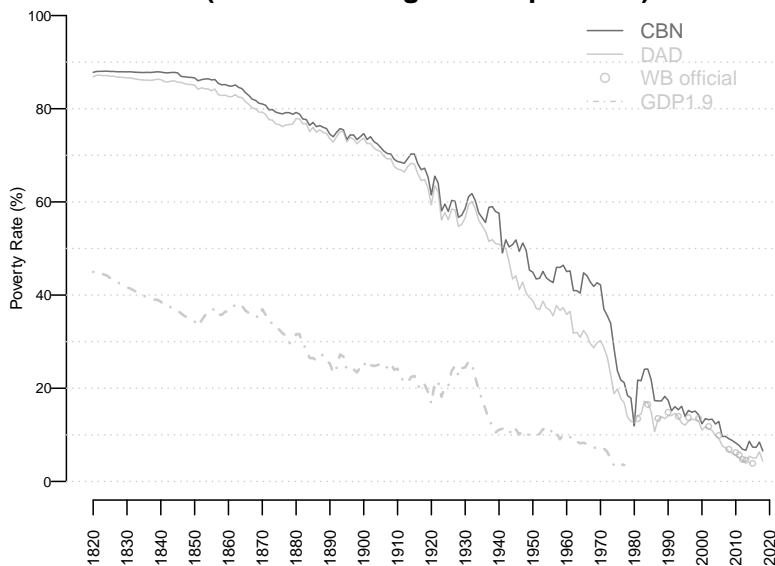
### (without the regional imputation)



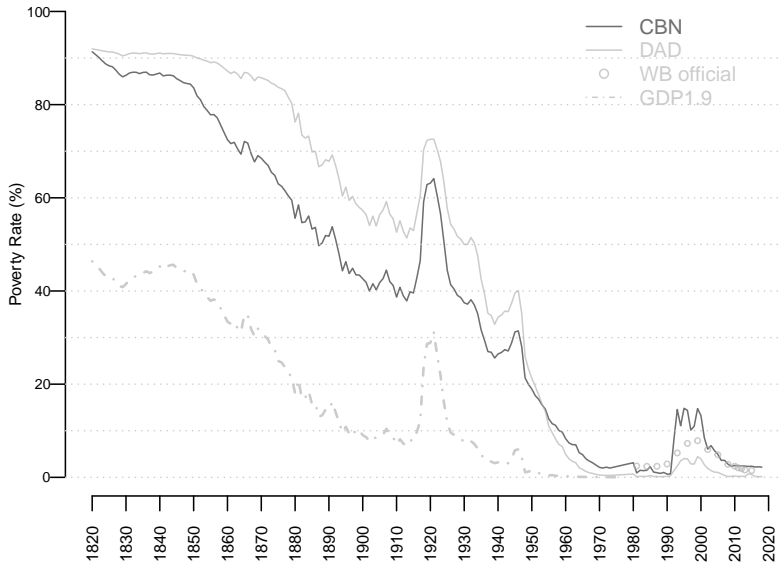
### Poverty Rates in Latin America and Carib.



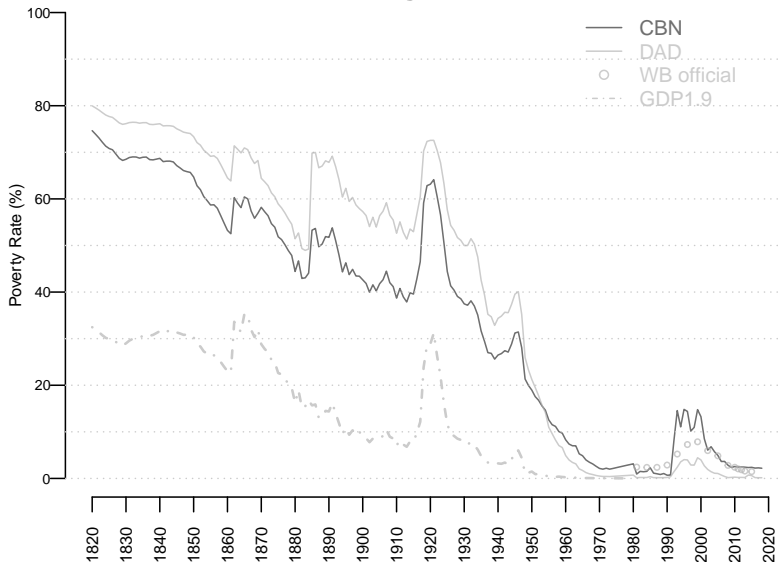
(without the regional imputation)



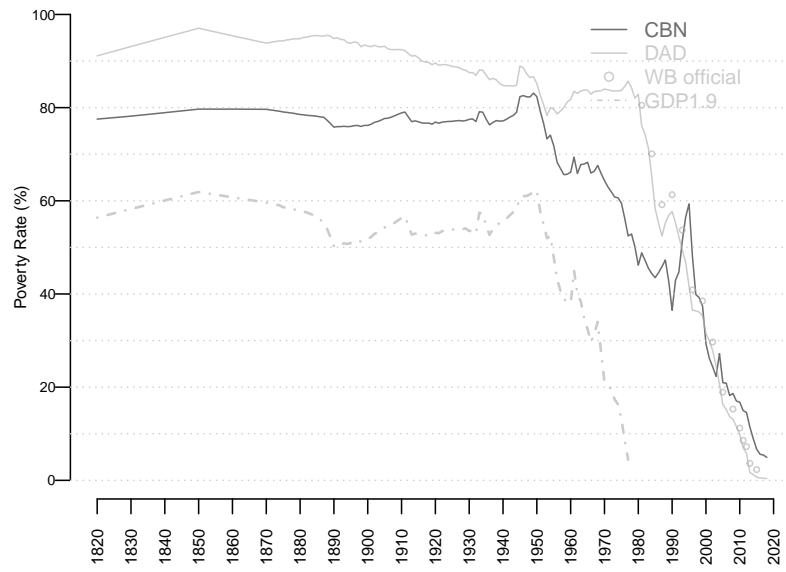
### Poverty Rates in East. Europe and form. SU



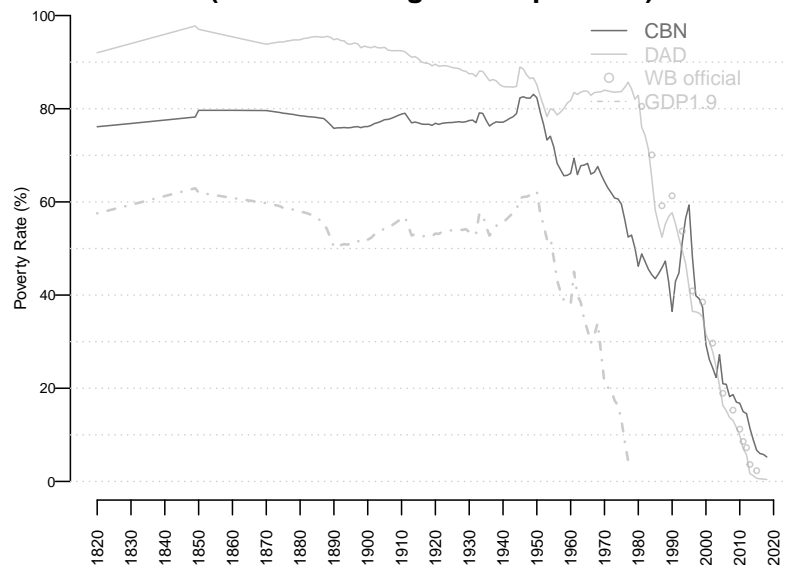
### (without the regional imputation)



### Poverty Rates in East Asia

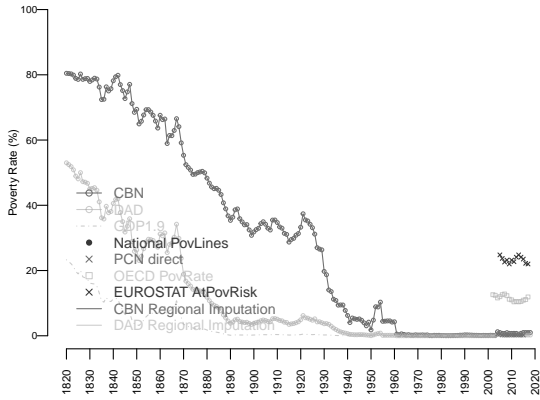


### (without the regional imputation)

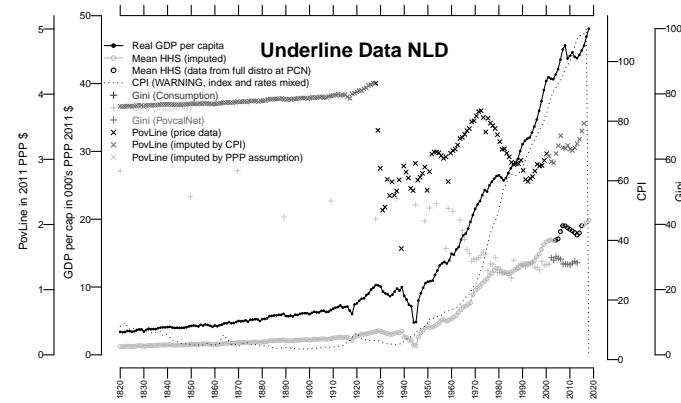
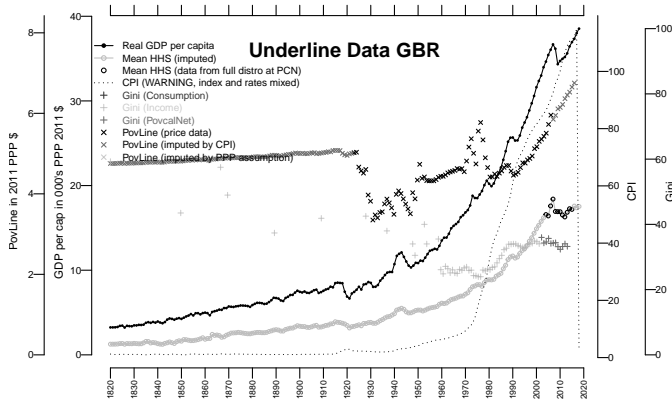
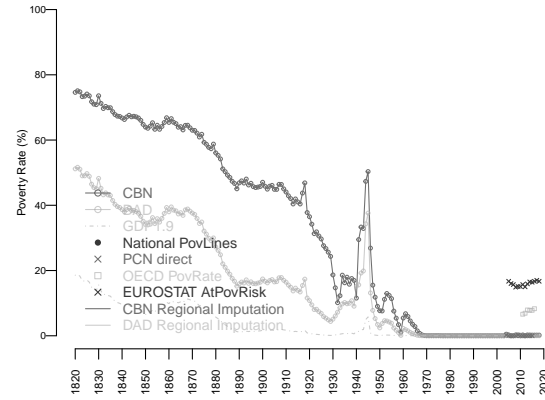


## 7.2.9 The Clio 25 focus countries

Poverty Rates in United Kingdom – GBR – W. Europe

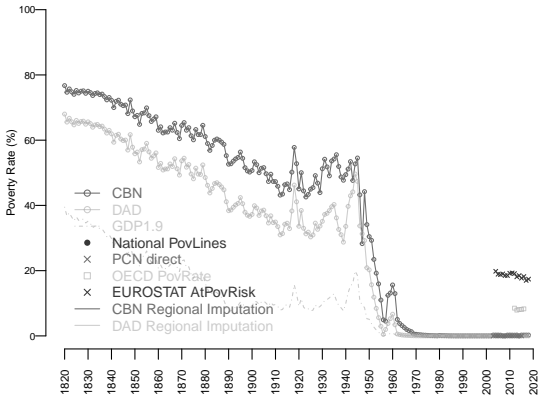


Poverty Rates in Netherlands – NLD – W. Europe

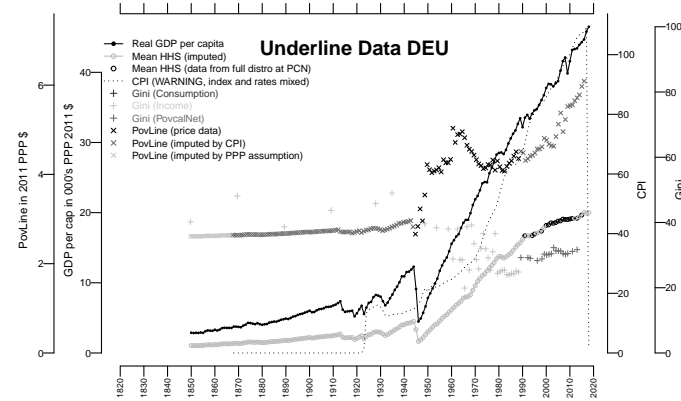
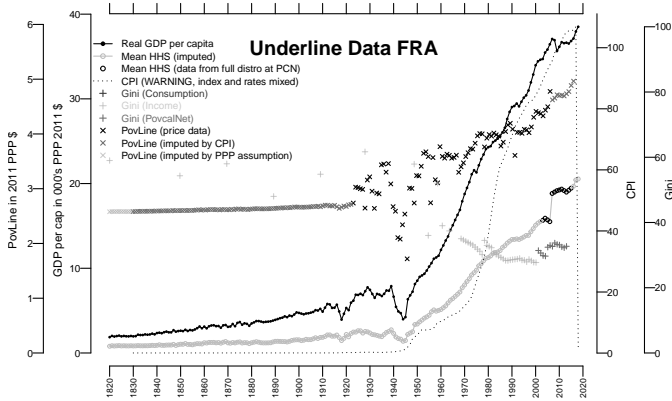
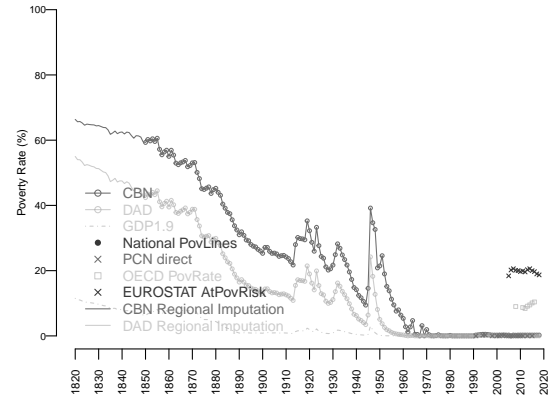




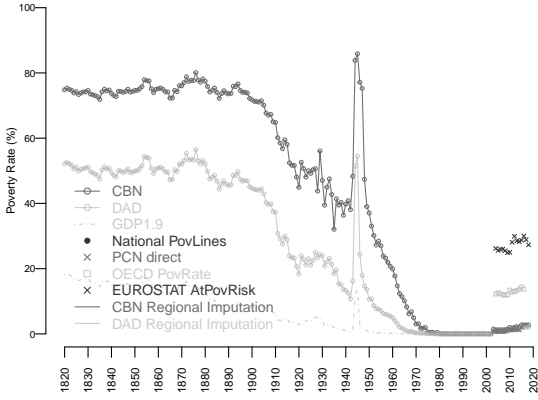
Poverty Rates in France – FRA – W. Europe



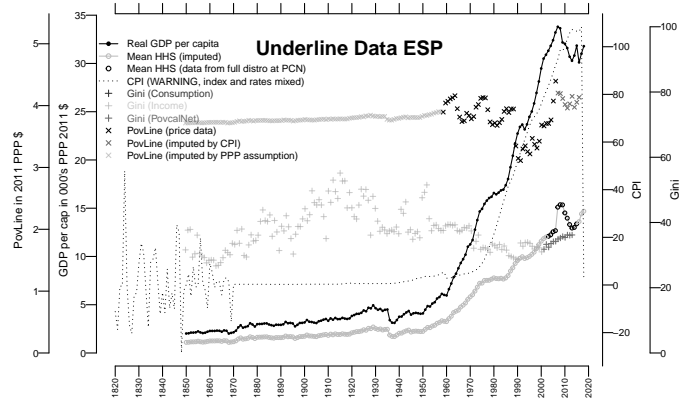
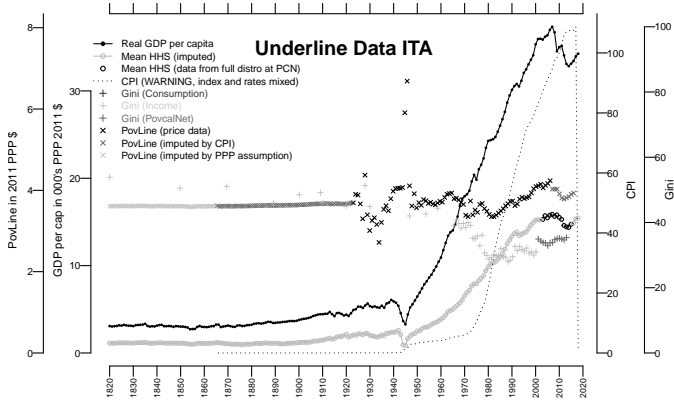
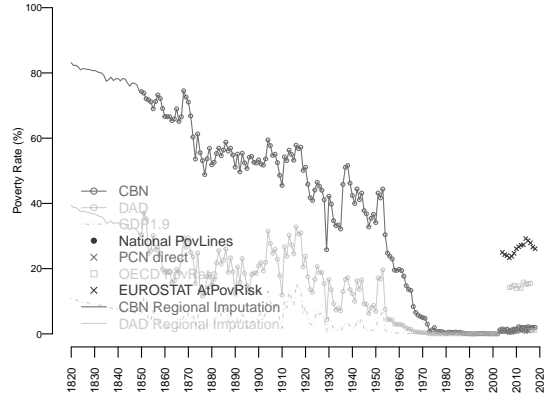
Poverty Rates in Germany – DEU – W. Europe



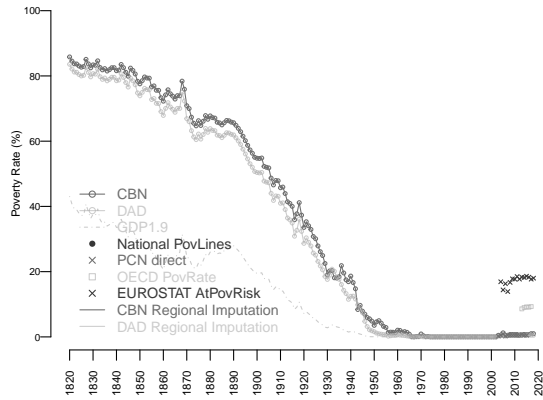
Poverty Rates in Italy – ITA – W. Europe



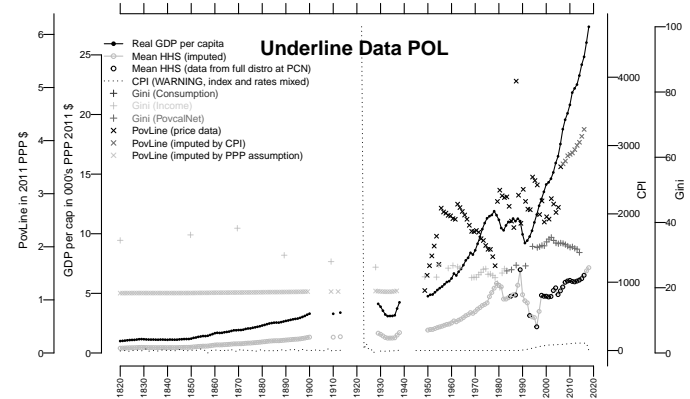
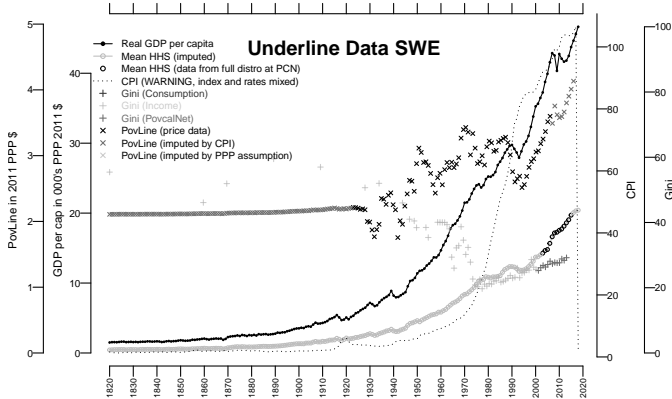
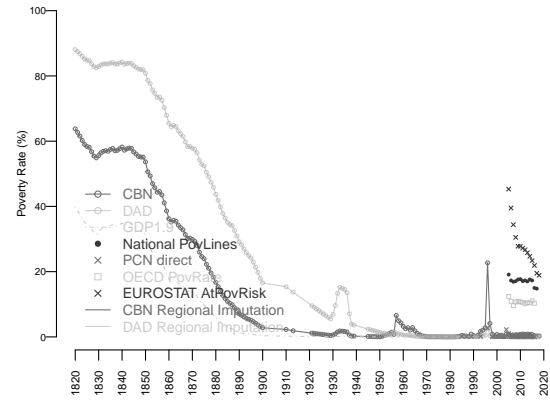
Poverty Rates in Spain – ESP – W. Europe



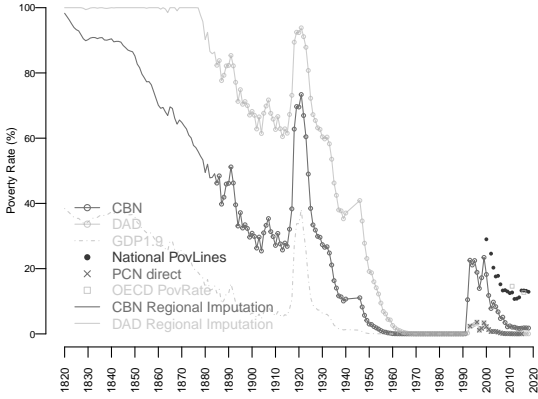
**Poverty Rates in Sweden – SWE – W. Europe**



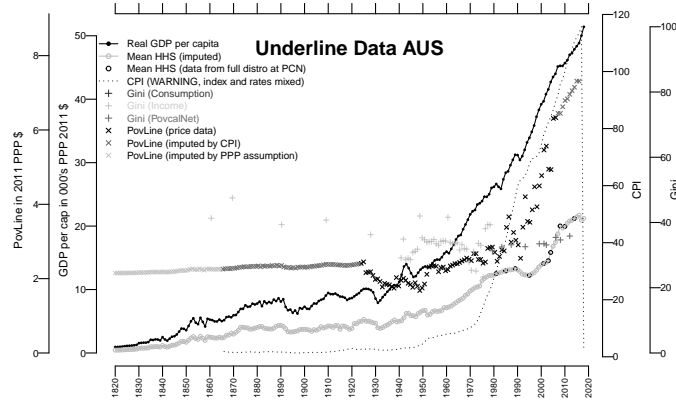
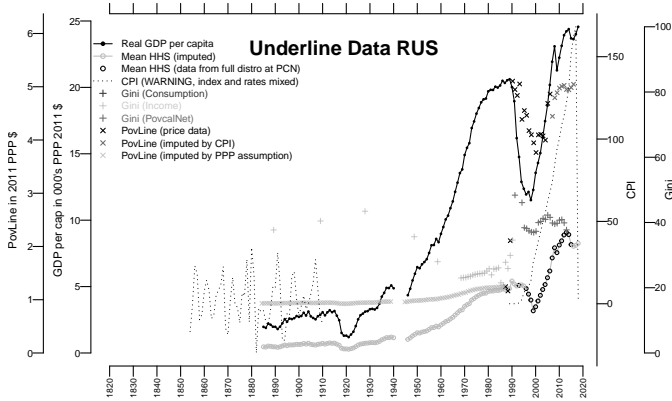
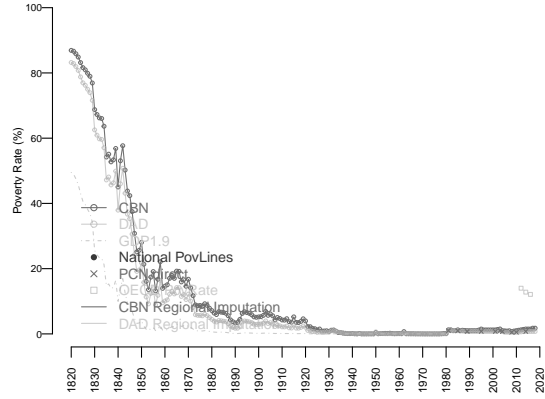
**Poverty Rates in Poland – POL – East. Europe and form. SU**



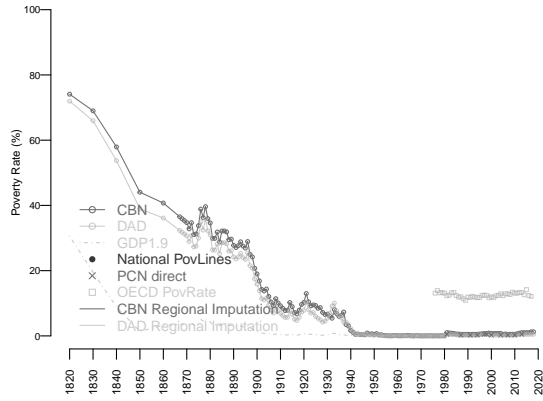
Poverty Rates in Russian Federation – RUS – East. Europe and form. St



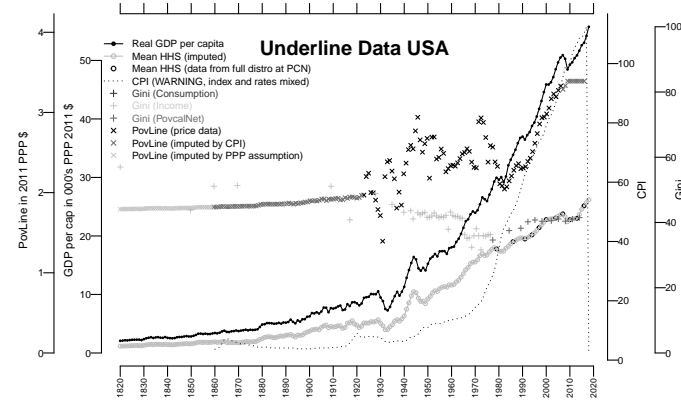
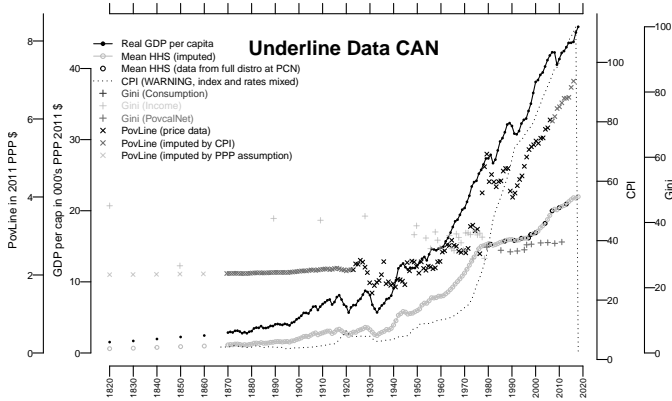
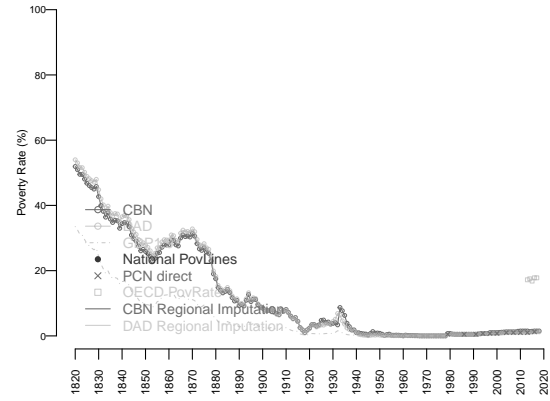
Poverty Rates in Australia – AUS – W. Offshoots



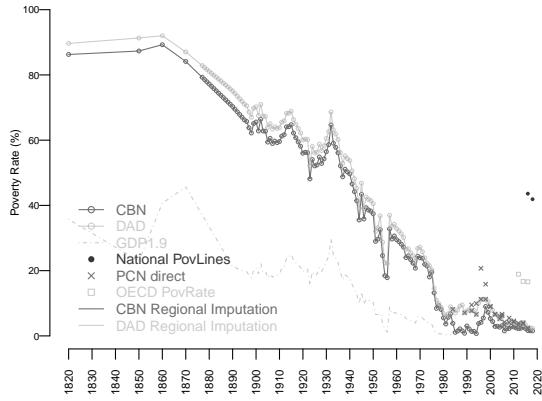
Poverty Rates in Canada – CAN – W. Offshoots



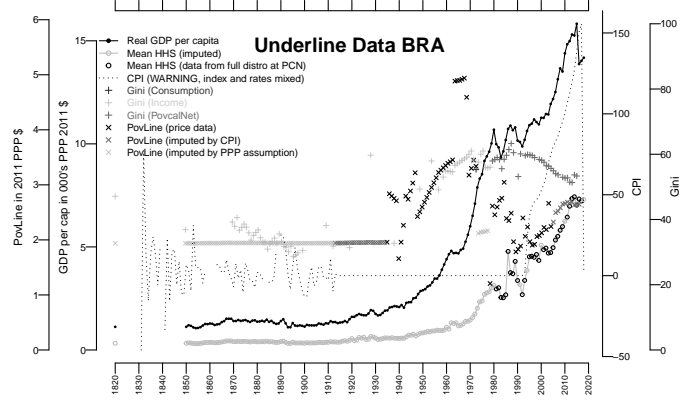
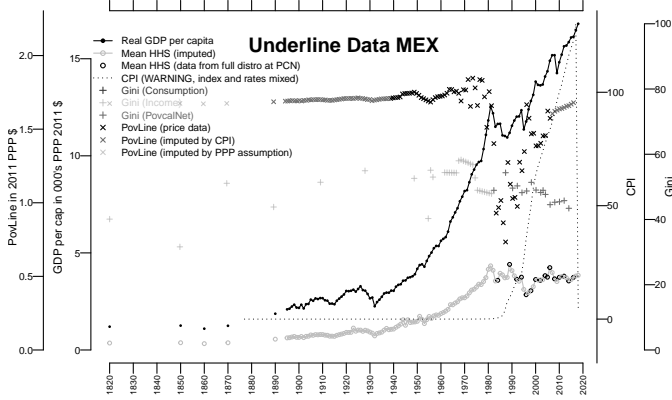
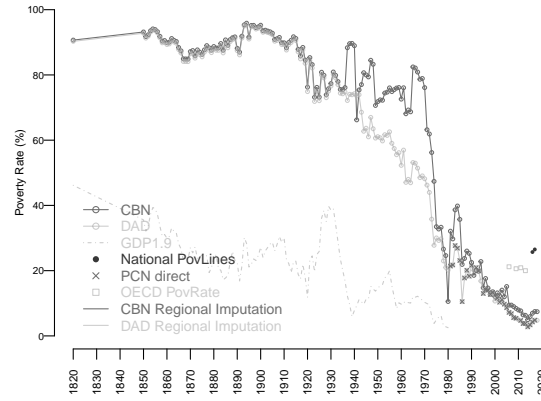
Poverty Rates in United States – USA – W. Offshoots



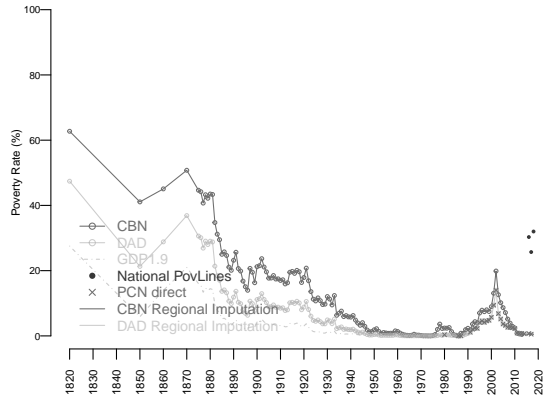
**Poverty Rates in Mexico – MEX – Latin America and Carib.**



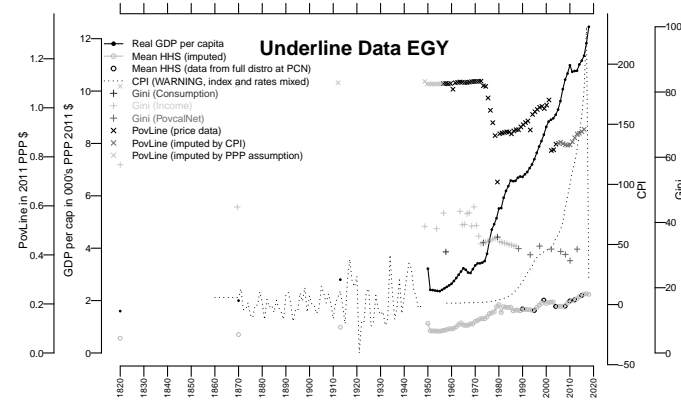
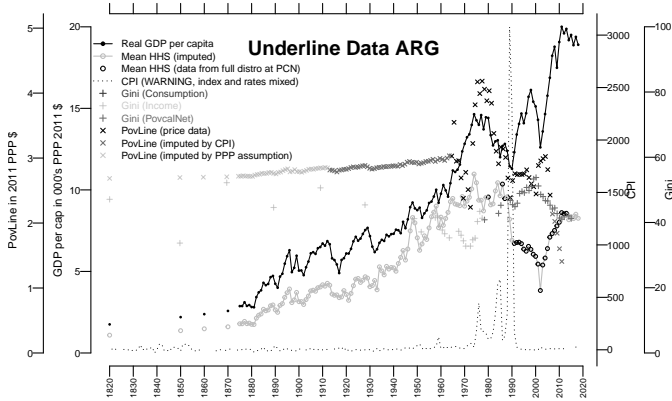
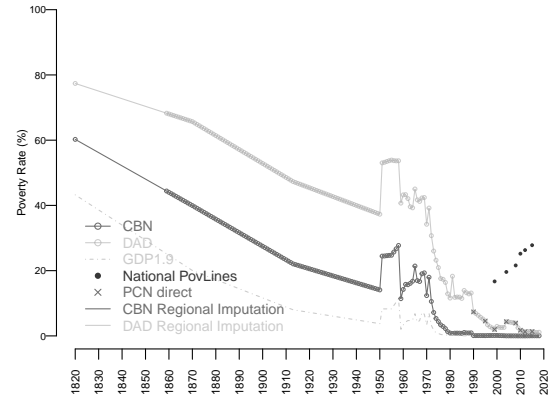
**Poverty Rates in Brazil – BRA – Latin America and Carib.**



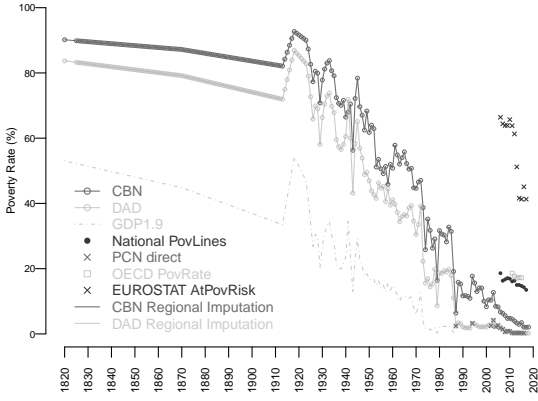
### Poverty Rates in Argentina – ARG – Latin America and Carib.



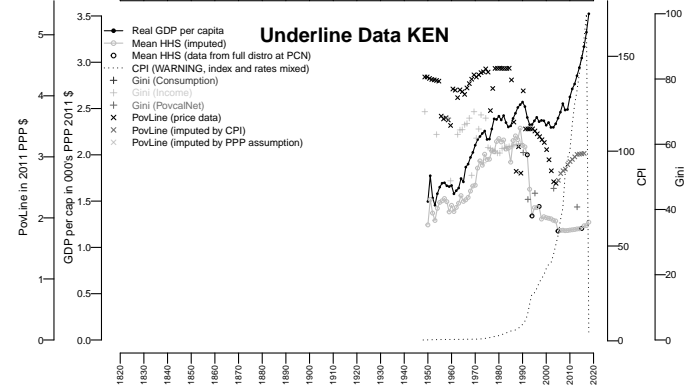
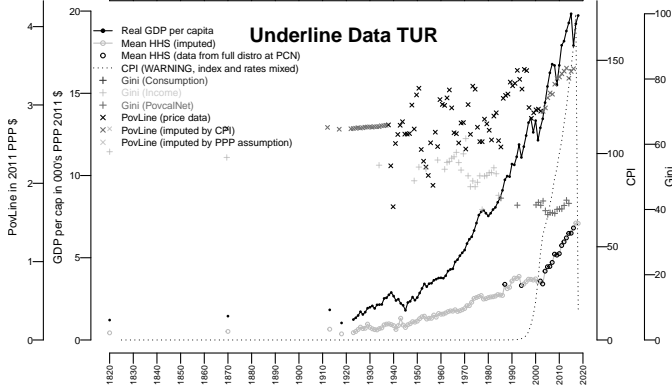
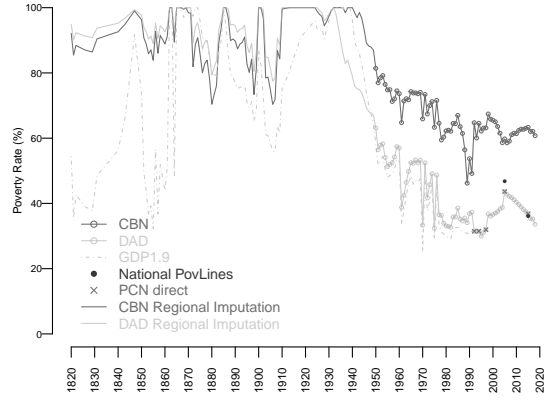
### Poverty Rates in Egypt – EGY – MENA



**Poverty Rates in Turkey – TUR – MENA**

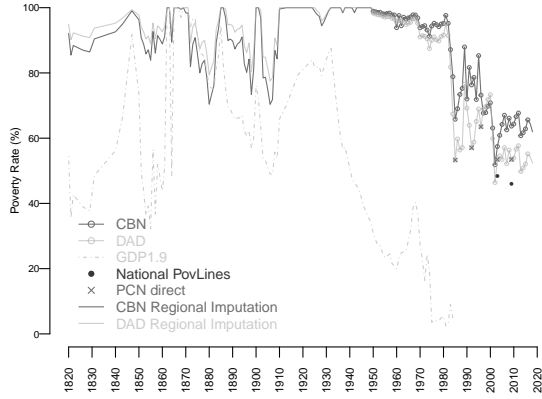


**Poverty Rates in Kenya – KEN – Sub-Saharan Africa**

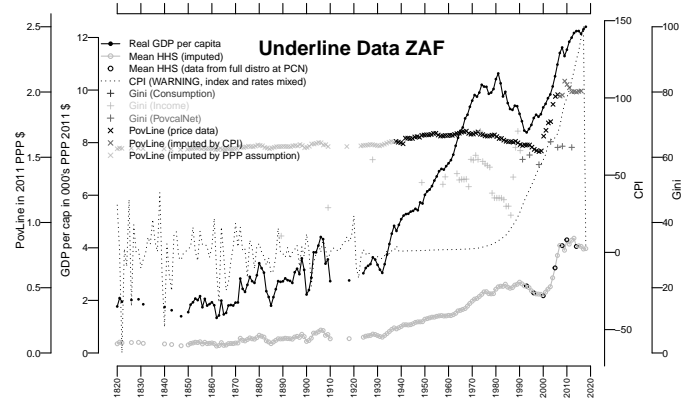
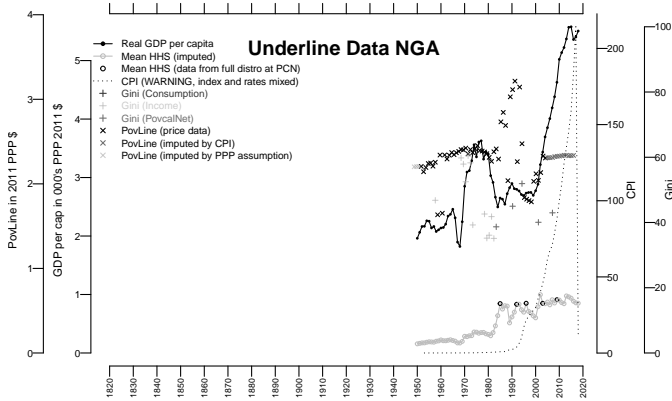
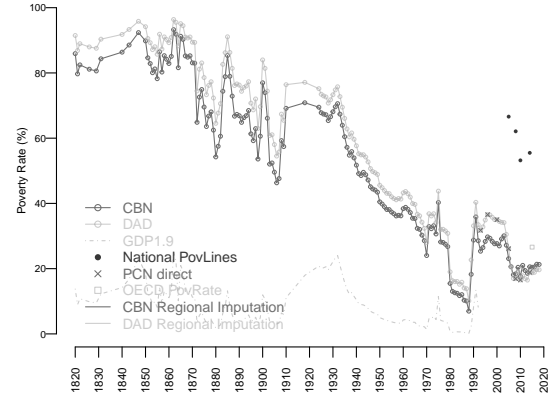




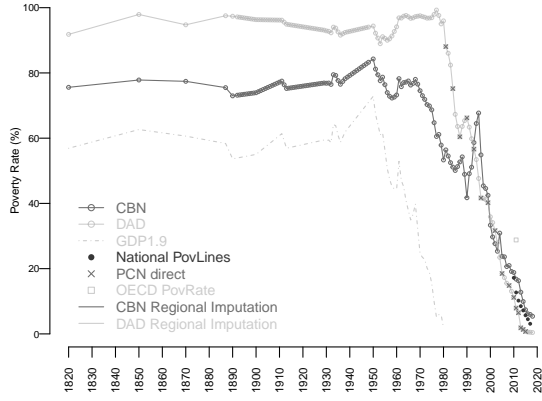
**Poverty Rates in Nigeria – NGA – Sub-Saharan Africa**



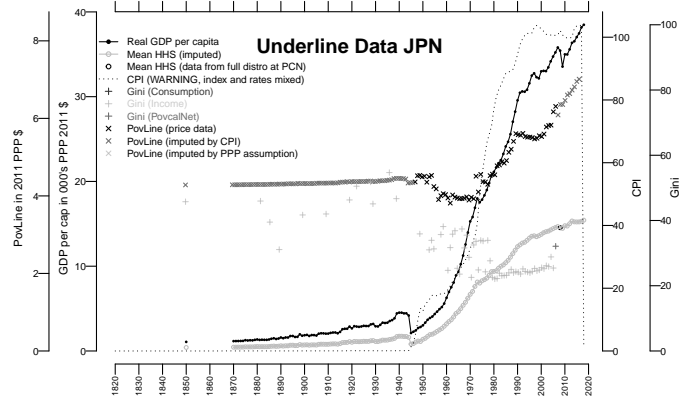
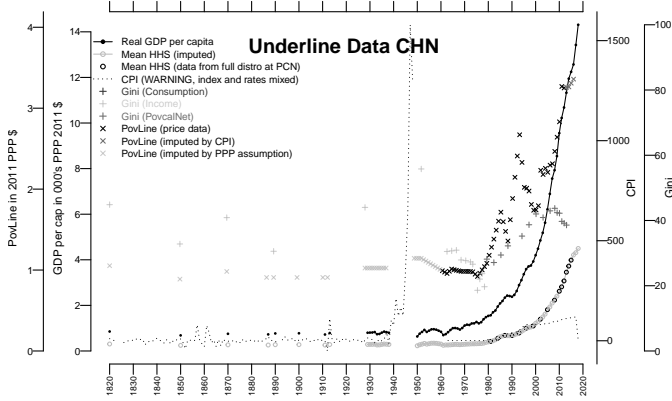
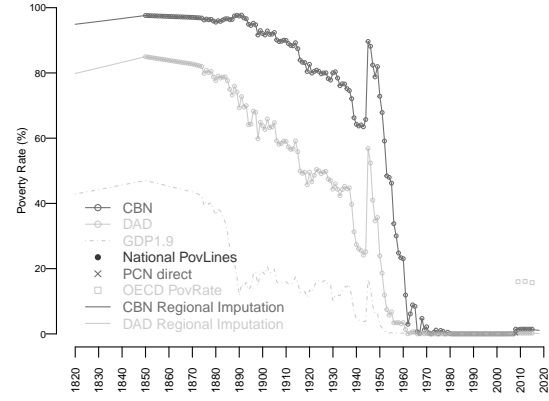
**Poverty Rates in South Africa – ZAF – Sub-Saharan Africa**



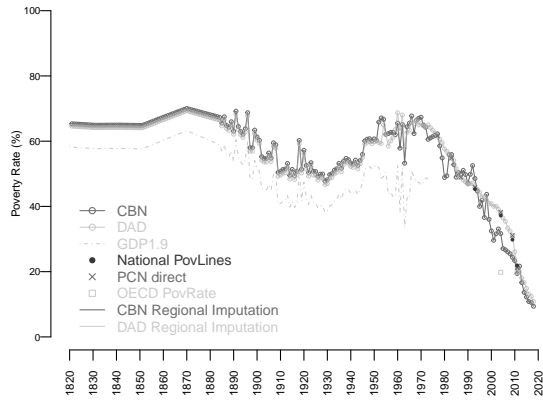
**Poverty Rates in China – CHN – East Asia**



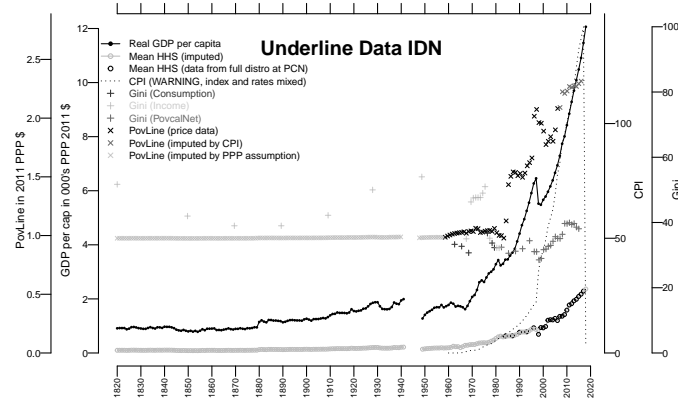
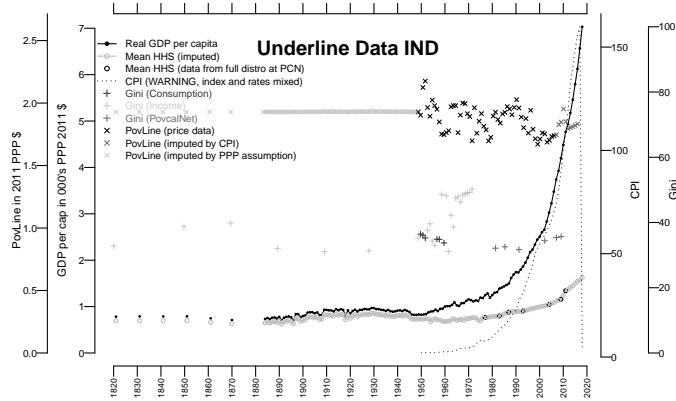
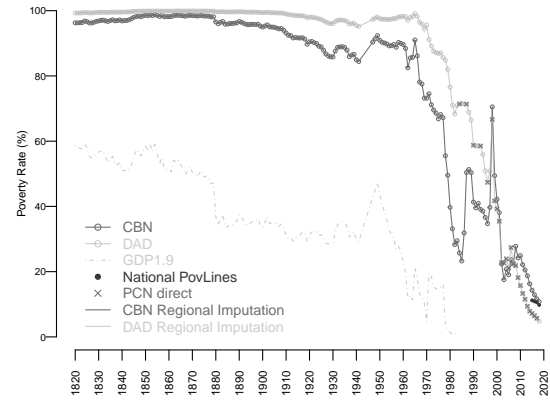
**Poverty Rates in Japan – JPN – East Asia**



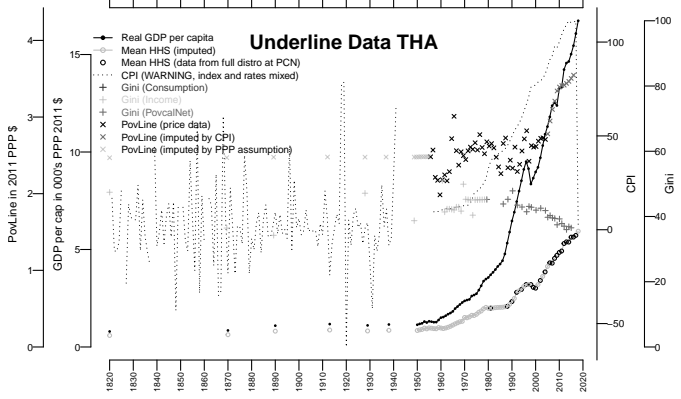
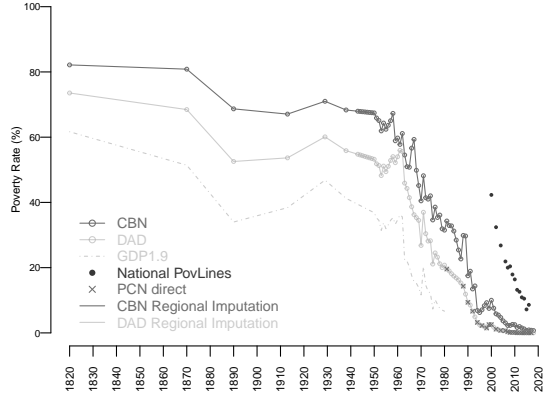
### Poverty Rates in India – IND – South and South–East Asia



### Poverty Rates in Indonesia – IDN – South and South–East Asia

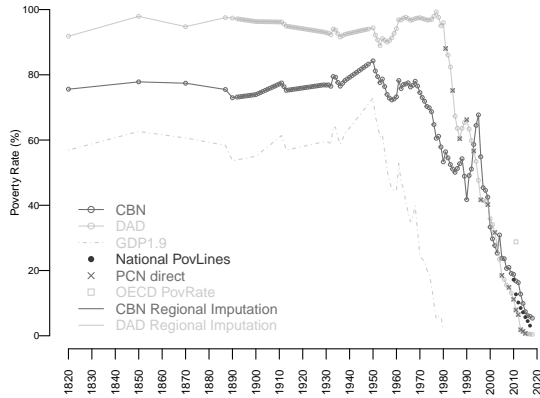


### Poverty Rates in Thailand – THA – South and South–East Asia

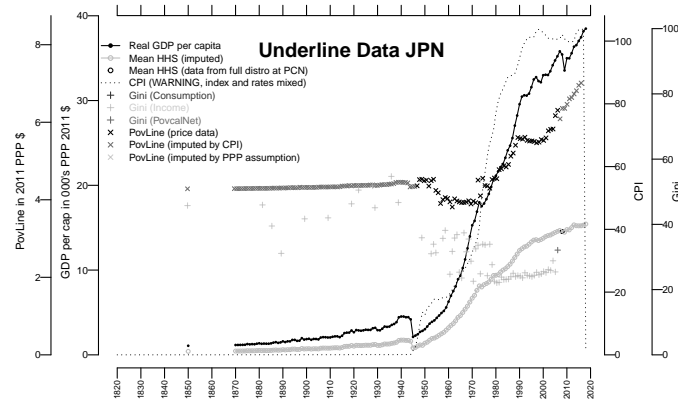
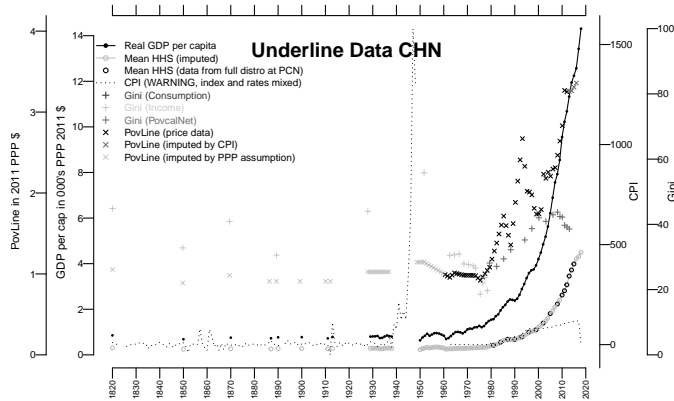
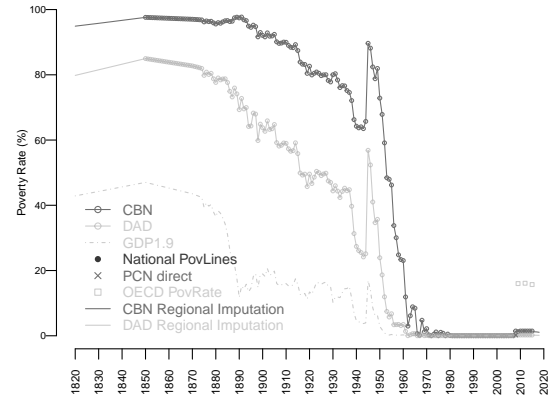


## 7.2.10 East Asia

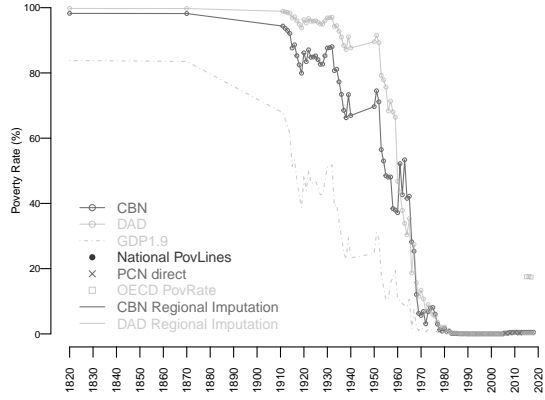
### Poverty Rates in China – CHN – East Asia



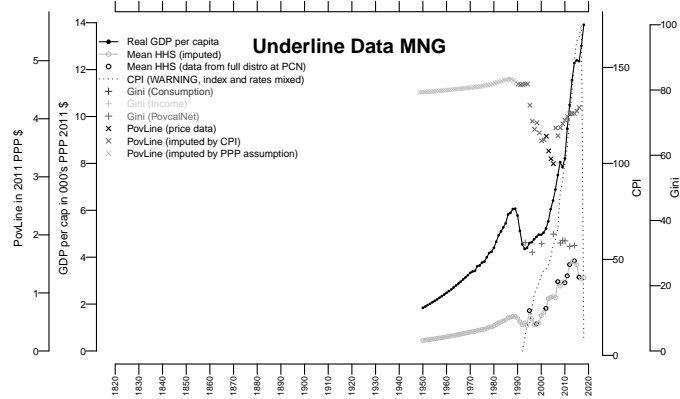
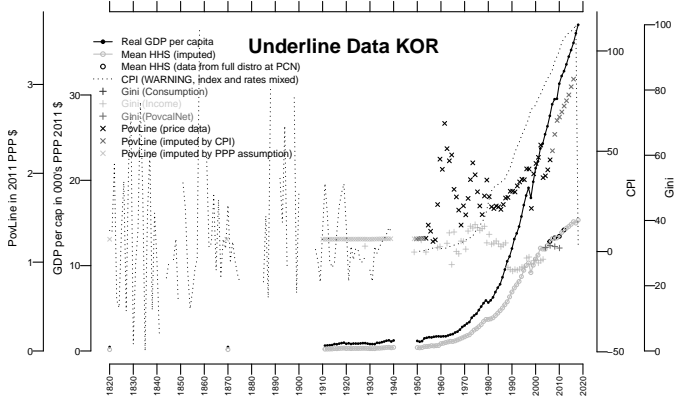
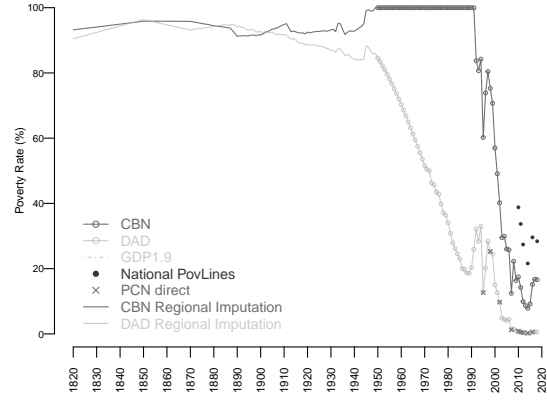
### Poverty Rates in Japan – JPN – East Asia



### Poverty Rates in Republic of Korea – KOR – East Asia

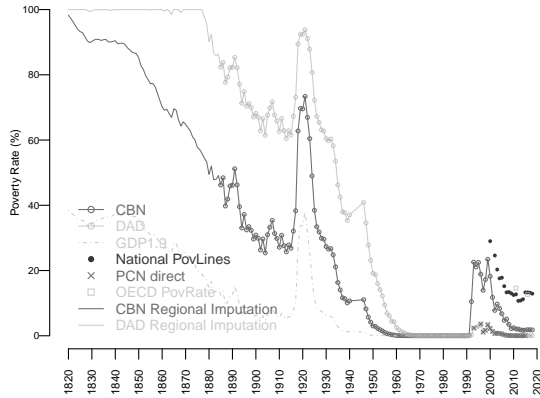


### Poverty Rates in Mongolia – MNG – East Asia

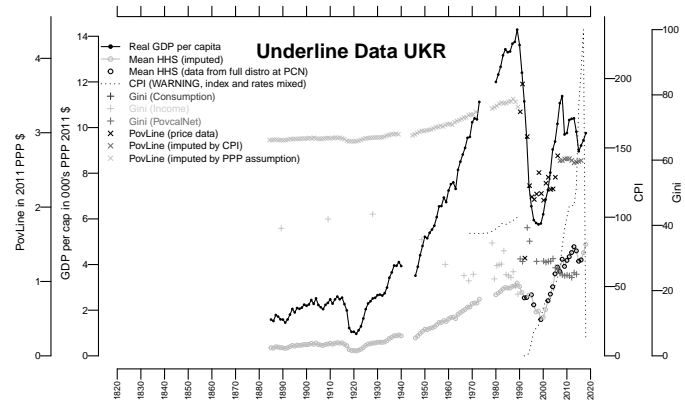
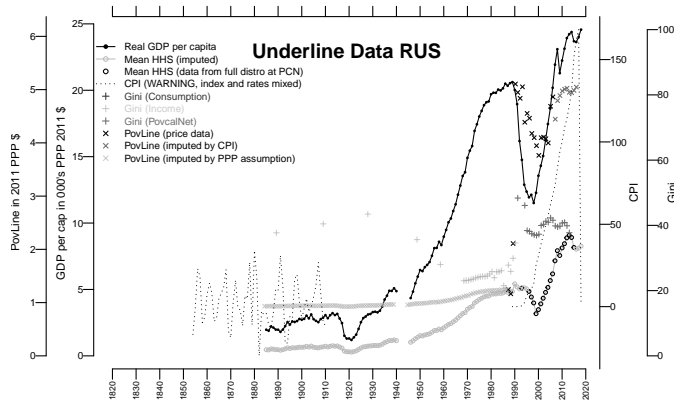
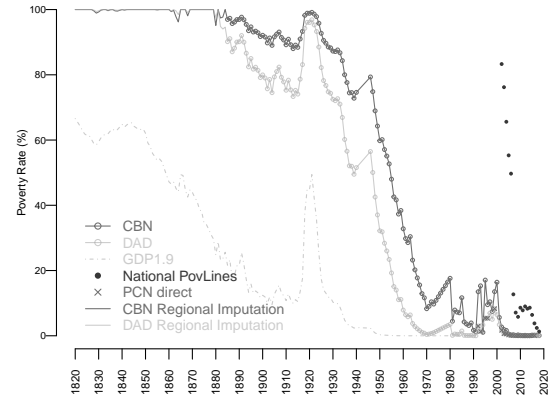


## 7.2.11 East. Europe and form. SU

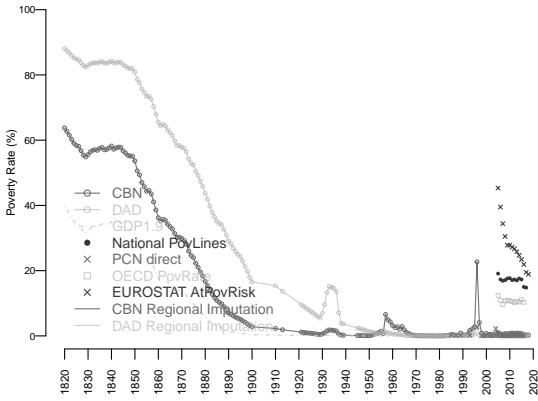
Poverty Rates in Russian Federation – RUS – East. Europe and form. SU



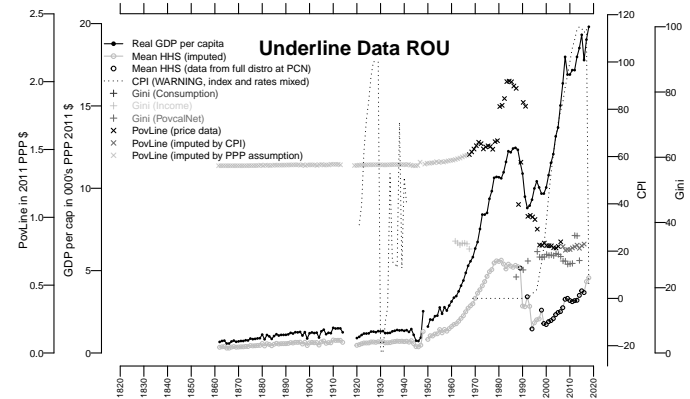
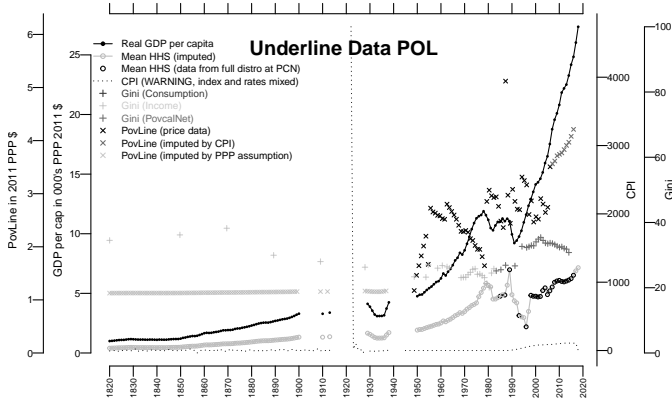
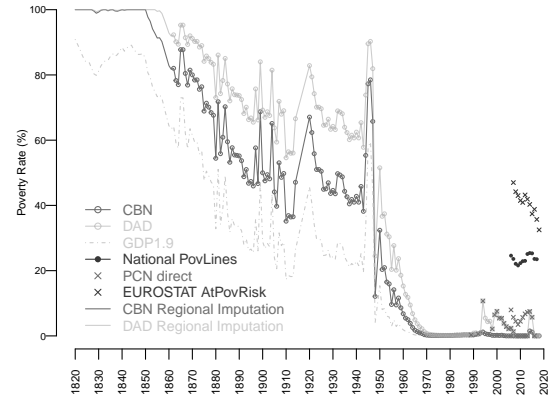
Poverty Rates in Ukraine – UKR – East. Europe and form. SU



### Poverty Rates in Poland – POL – East. Europe and form. SU

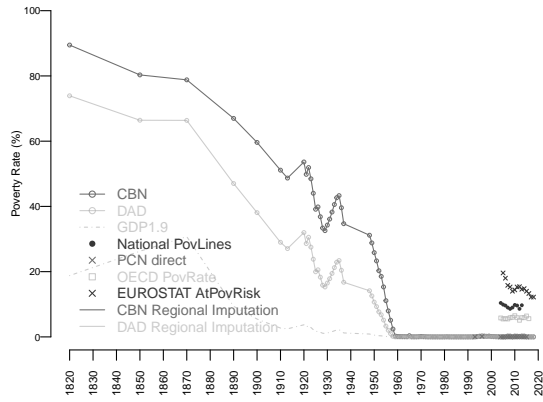


### Poverty Rates in Romania – ROU – East. Europe and form. SU

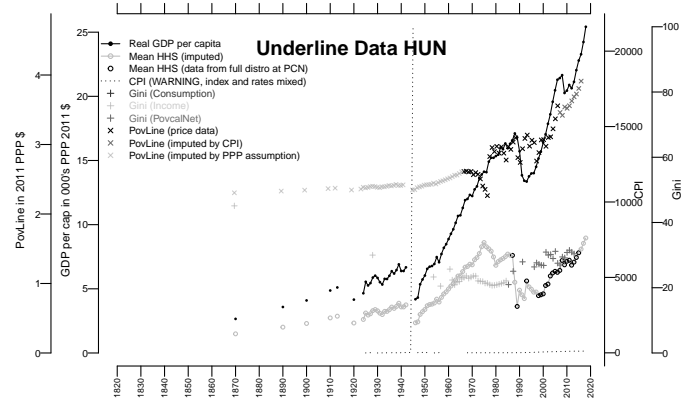
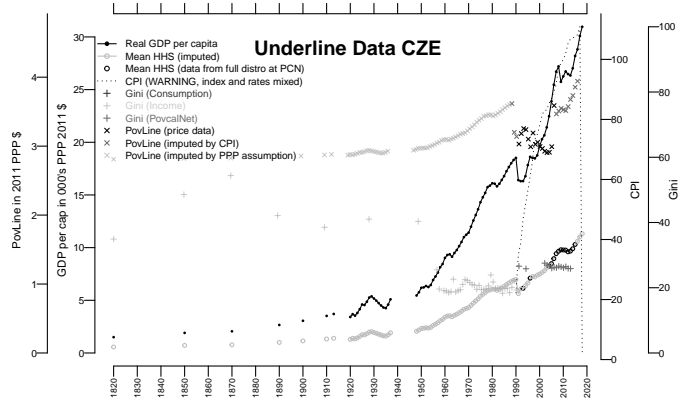
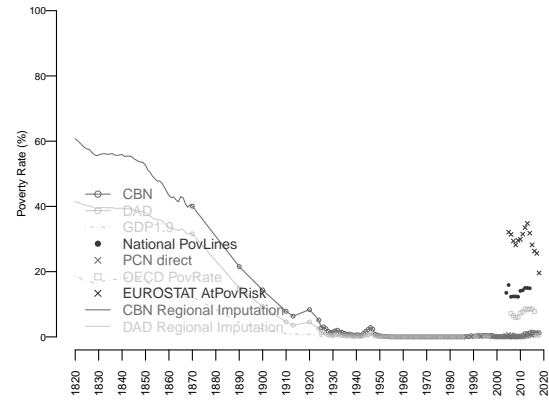




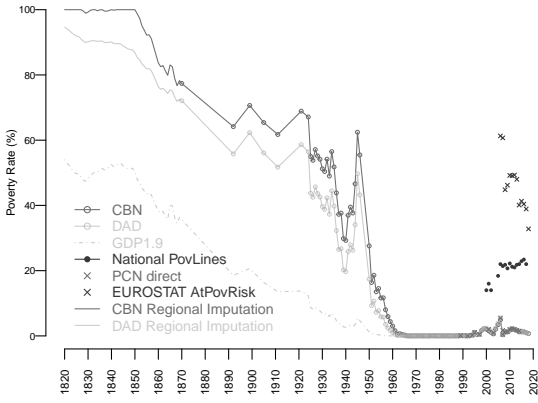
### Poverty Rates in Czech Republic – CZE – East. Europe and form. SU



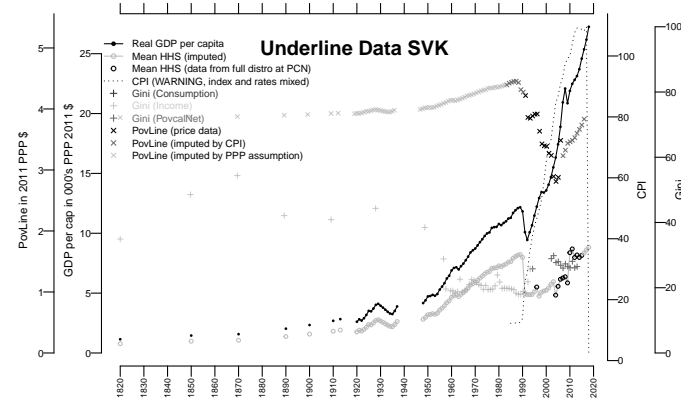
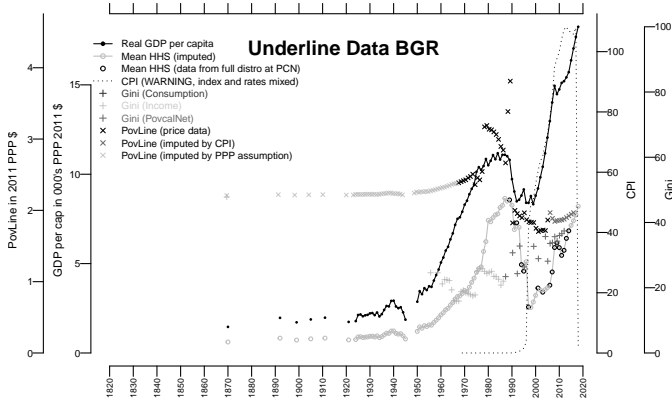
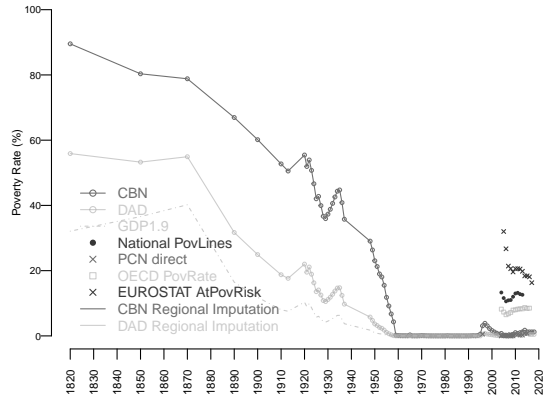
### Poverty Rates in Hungary – HUN – East. Europe and form. SU



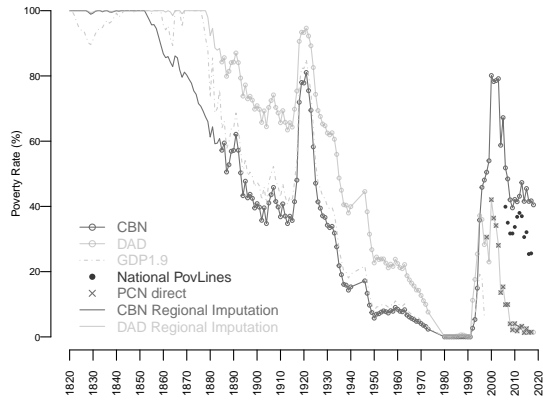
### Poverty Rates in Bulgaria – BGR – East. Europe and form. SU



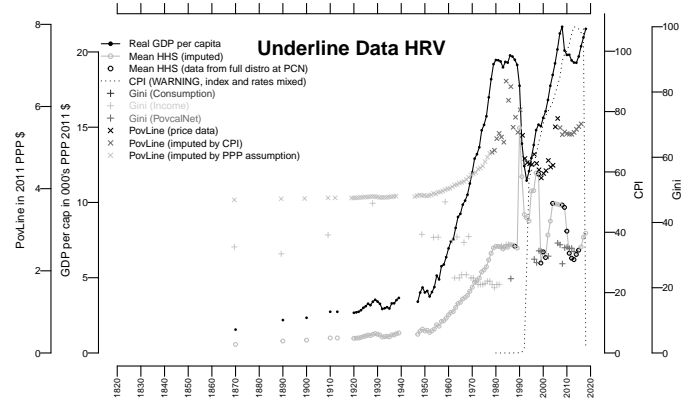
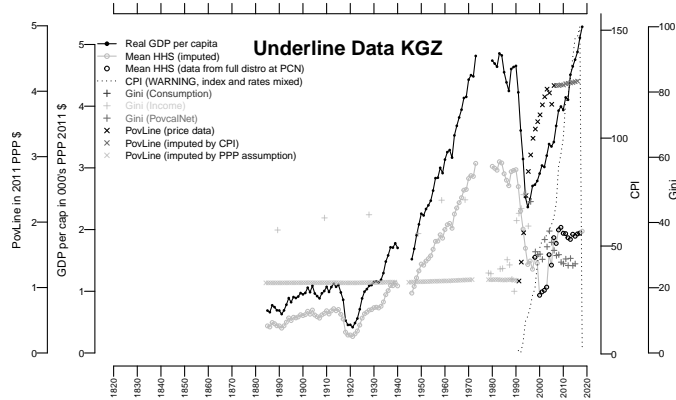
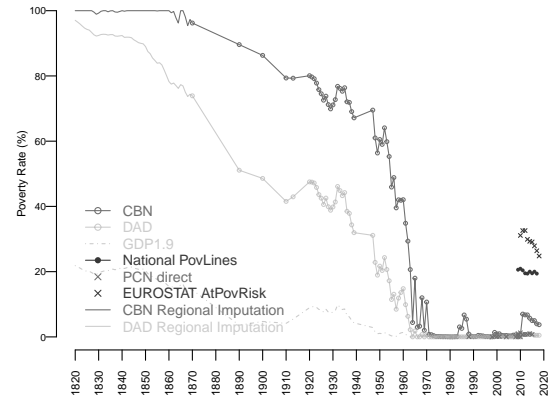
### Poverty Rates in Slovakia – SVK – East. Europe and form. SU



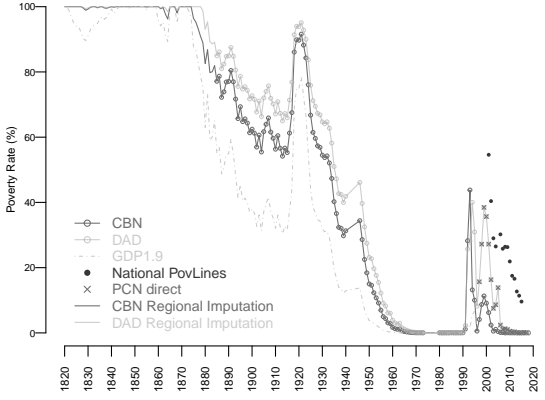
### Poverty Rates in Kyrgyzstan – KGZ – East. Europe and form. SU



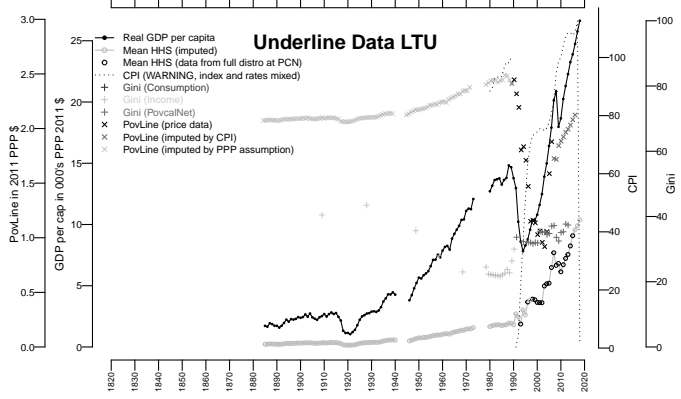
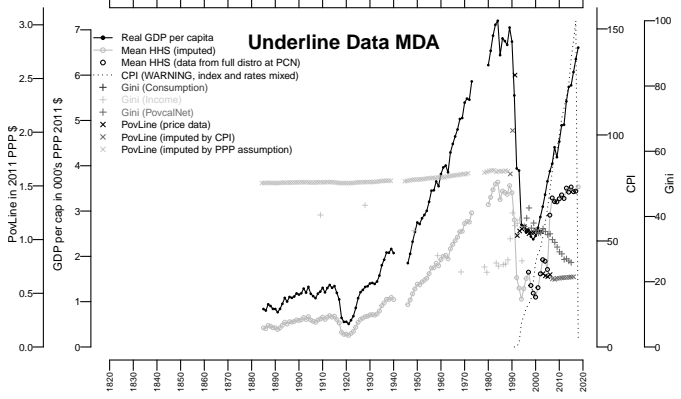
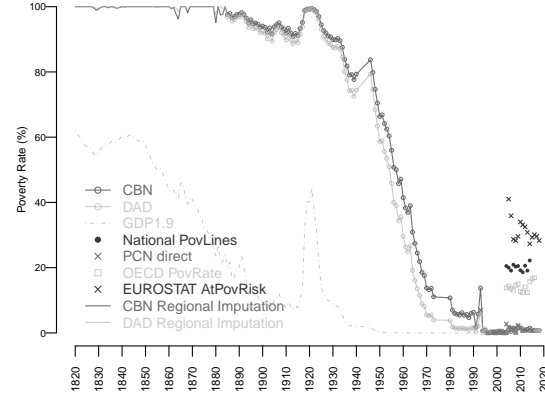
### Poverty Rates in Croatia – HRV – East. Europe and form. SU



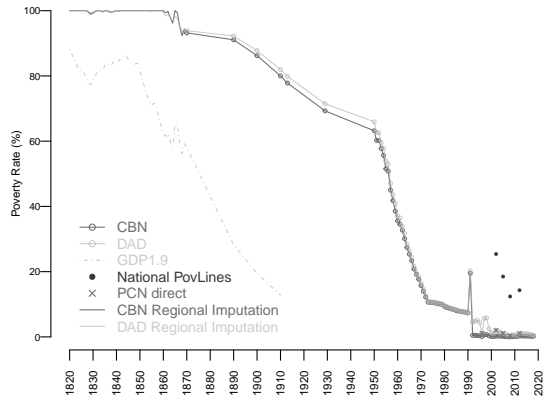
overty Rates in Republic of Moldova – MDA – East. Europe and form. S



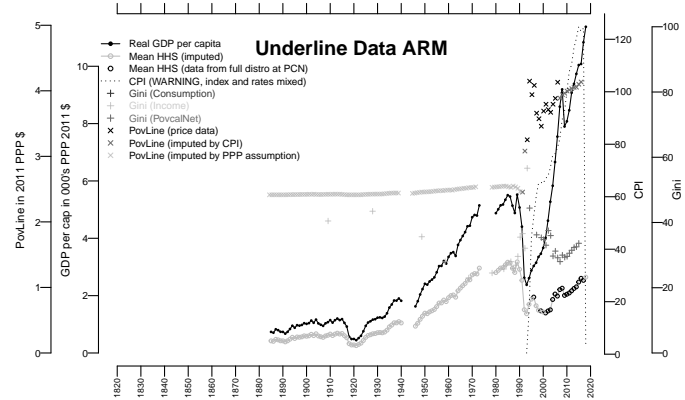
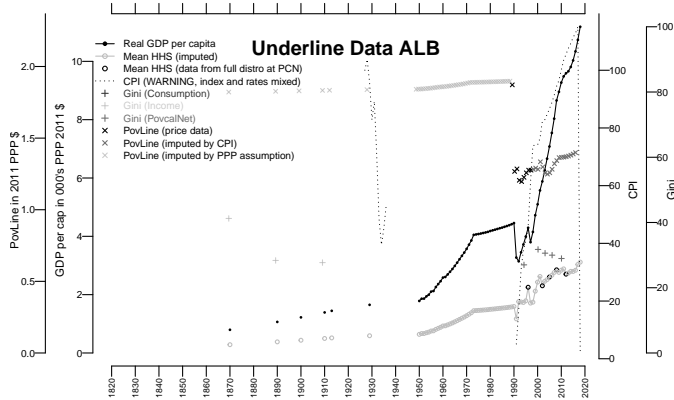
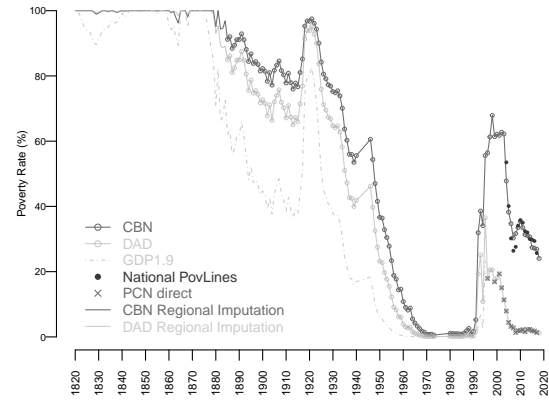
Poverty Rates in Lithuania – LTU – East. Europe and form. S



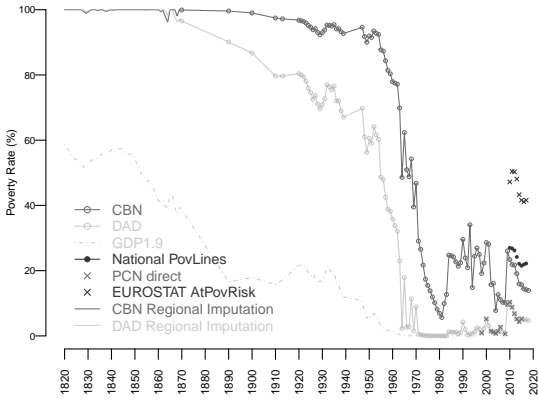
Poverty Rates in Albania – ALB – East. Europe and form. SU



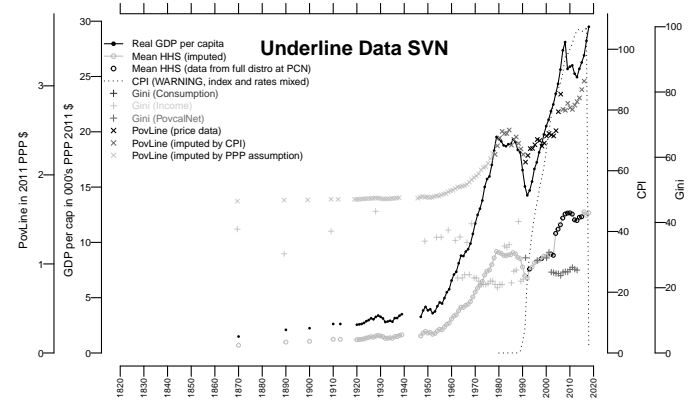
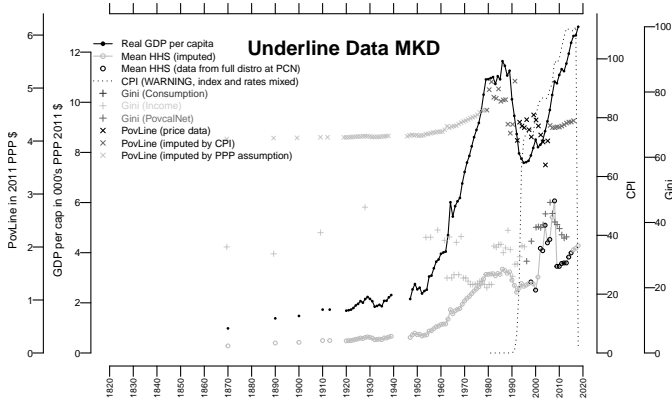
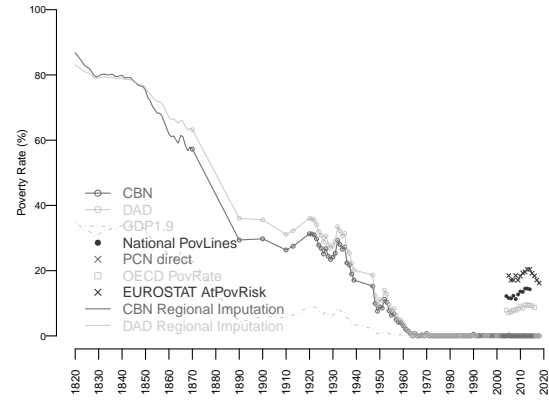
Poverty Rates in Armenia – ARM – East. Europe and form. SU



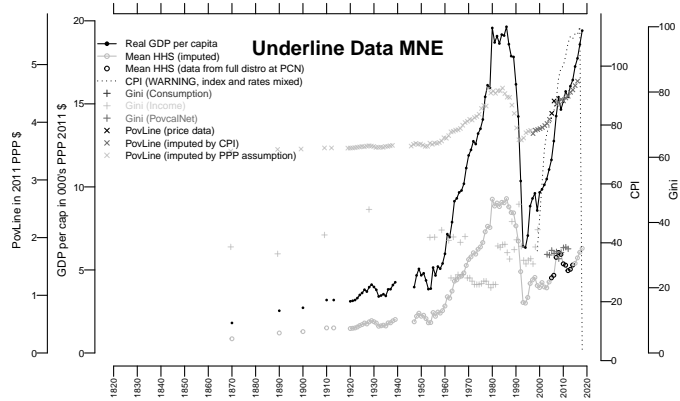
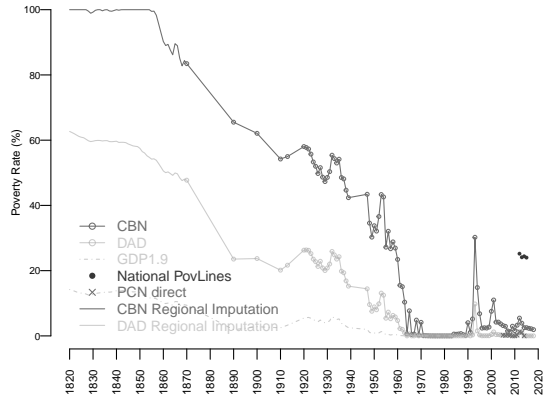
Poverty Rates in TFYR of Macedonia – MKD – East. Europe and form. SI



Poverty Rates in Slovenia – SVN – East. Europe and form. SU

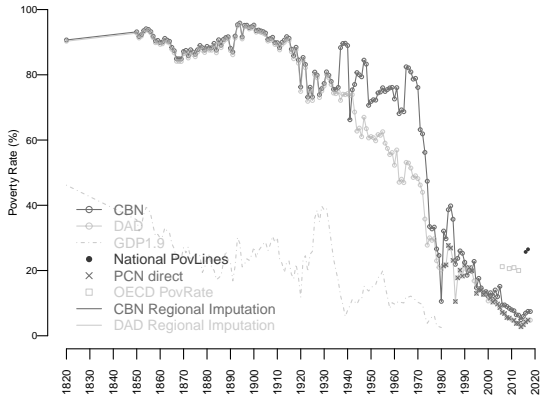


### Poverty Rates in Montenegro – MNE – East. Europe and form. SU

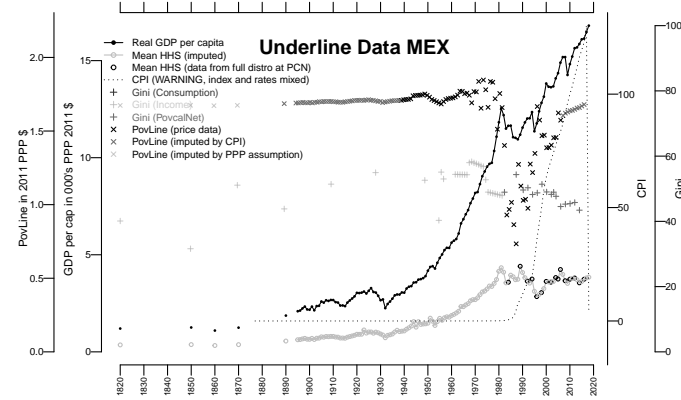
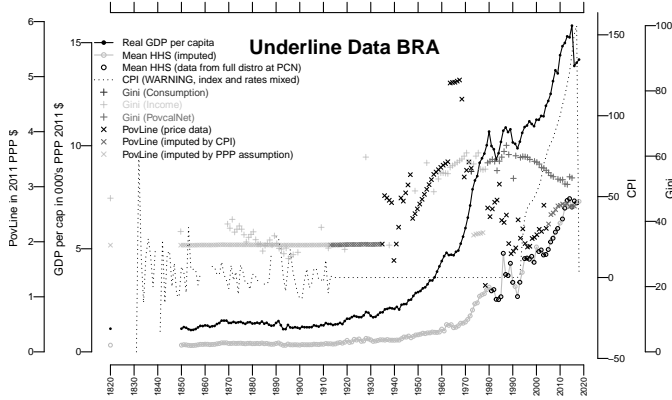
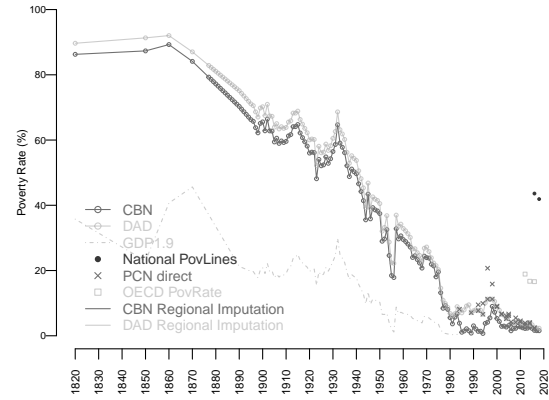


## 7.2.12 Latin America and Carib.

Poverty Rates in Brazil – BRA – Latin America and Carib.

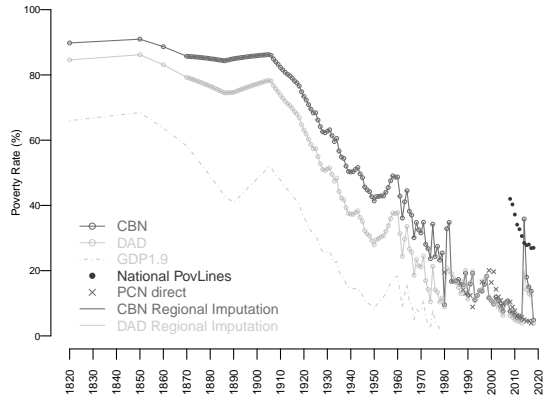


Poverty Rates in Mexico – MEX – Latin America and Carib.

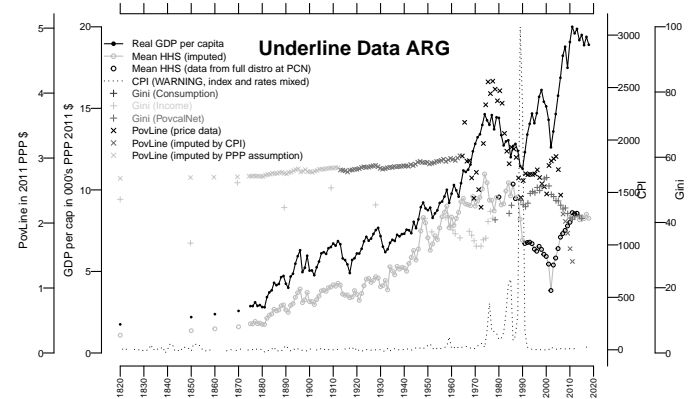
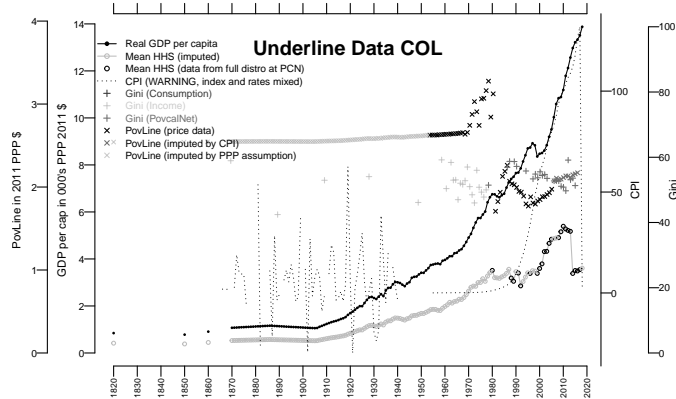
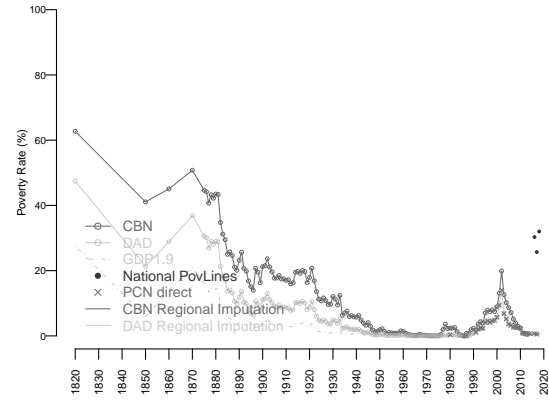




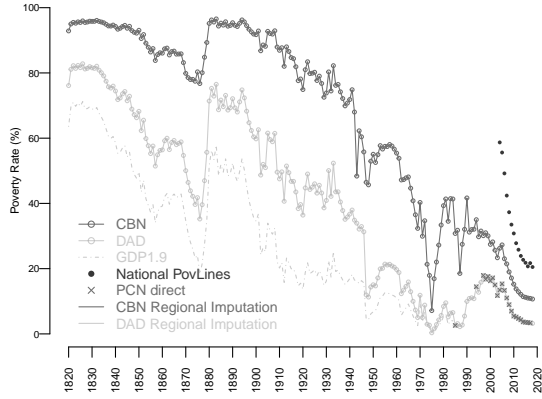
Poverty Rates in Colombia – COL – Latin America and Carib.



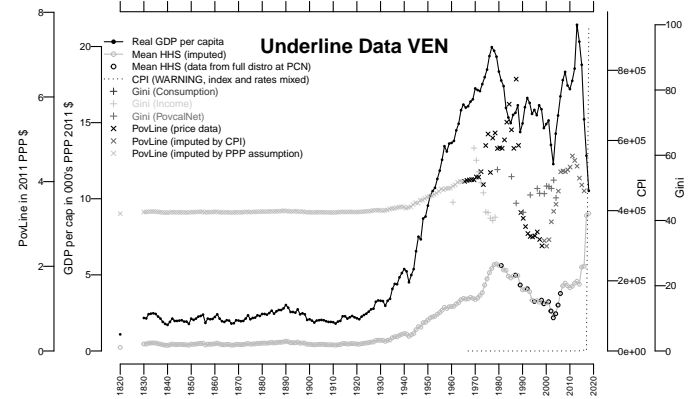
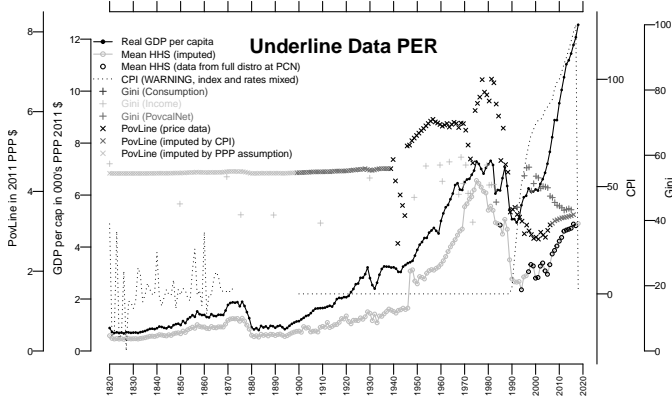
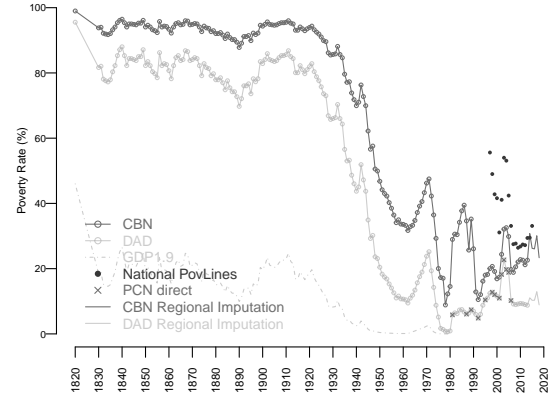
Poverty Rates in Argentina – ARG – Latin America and Carib.



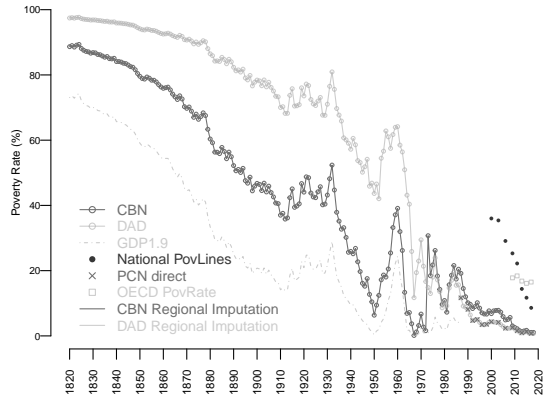
Poverty Rates in Peru – PER – Latin America and Carib.



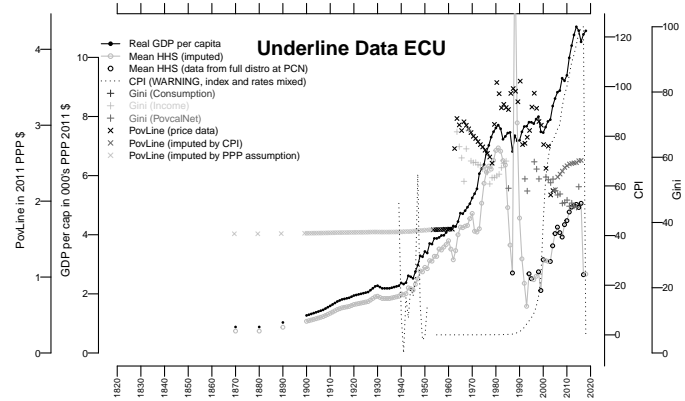
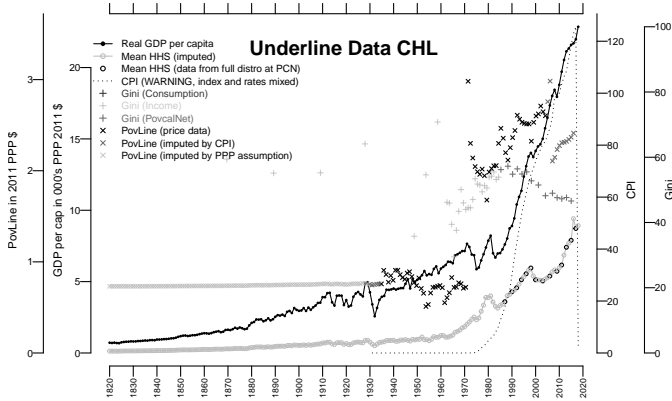
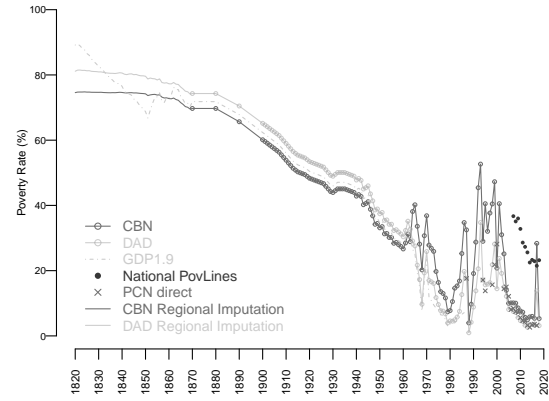
Rates in Venezuela (Bolivarian Republic of) – VEN – Latin America and



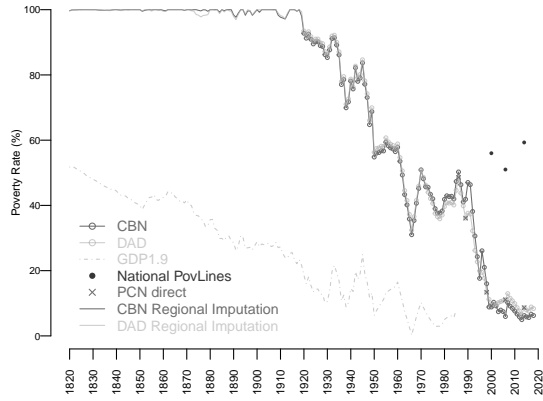
Poverty Rates in Chile – CHL – Latin America and Carib.



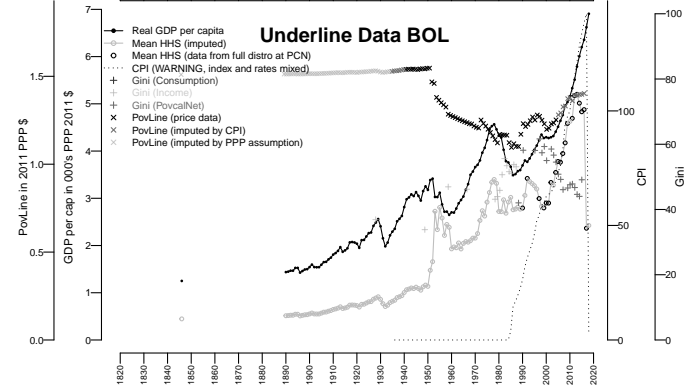
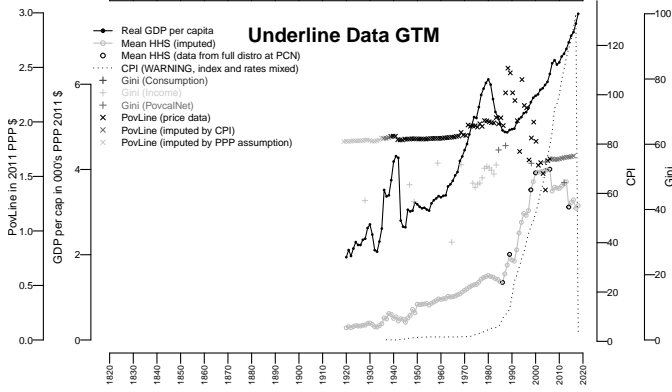
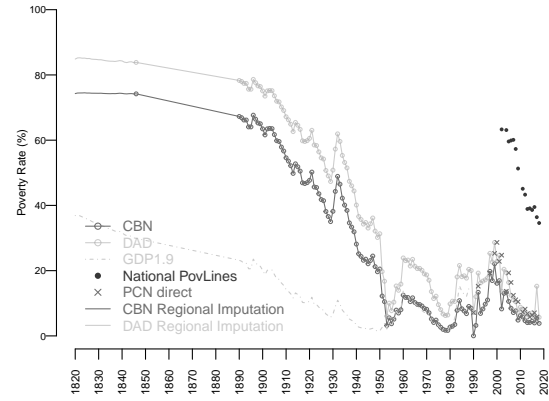
Poverty Rates in Ecuador – ECU – Latin America and Carib.



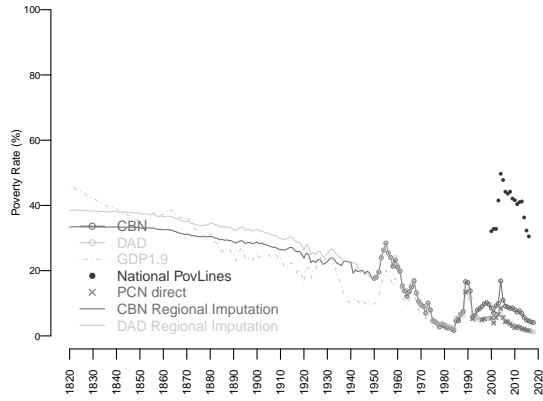
**Poverty Rates in Guatemala – GTM – Latin America and Carib.**



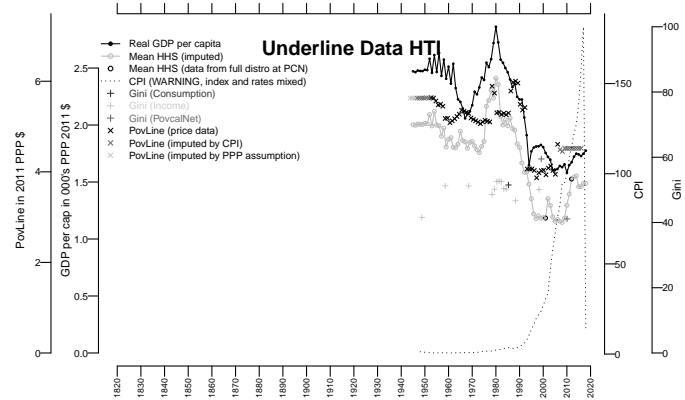
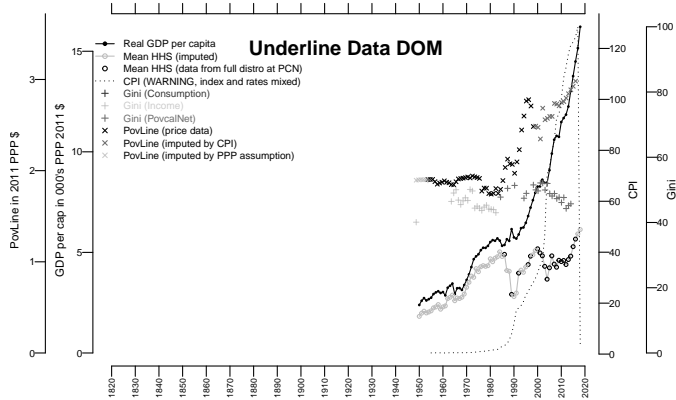
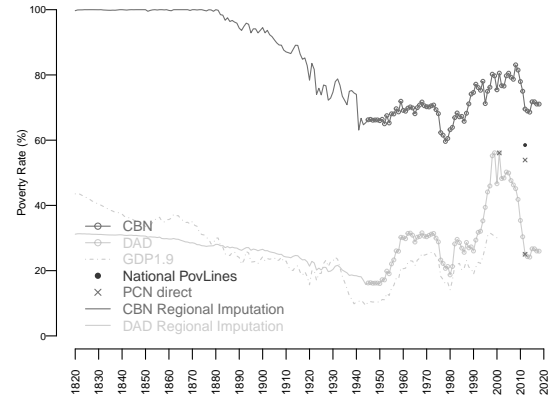
**erty Rates in Bolivia (Plurinational State of) – BOL – Latin America and C**



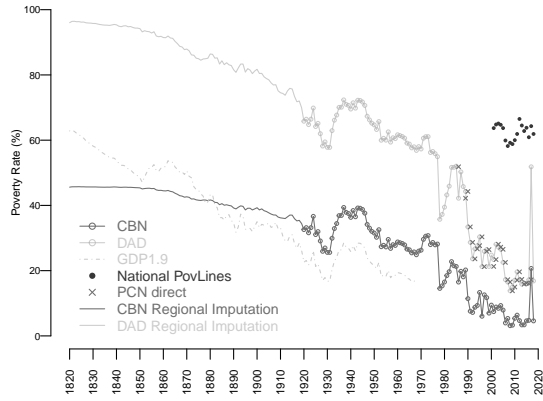
### Poverty Rates in Dominican Republic – DOM – Latin America and Carib



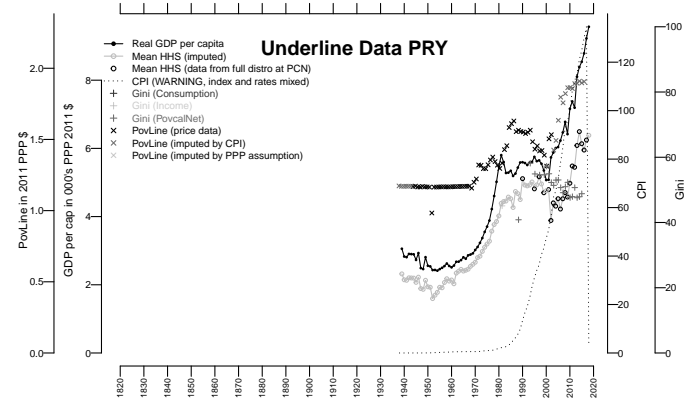
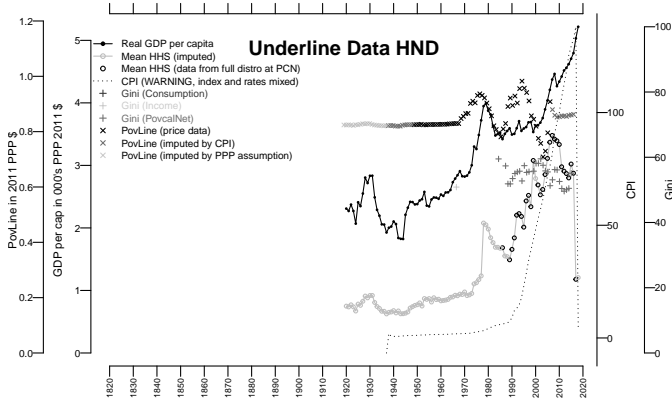
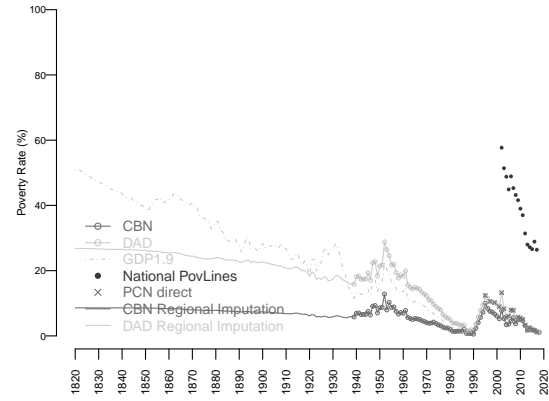
### Poverty Rates in Haiti – HTI – Latin America and Carib



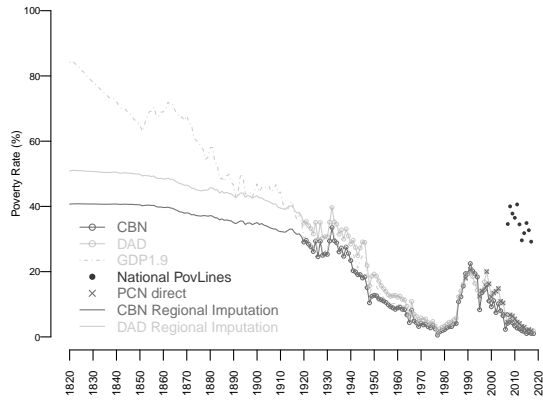
Poverty Rates in Honduras – HND – Latin America and Carib.



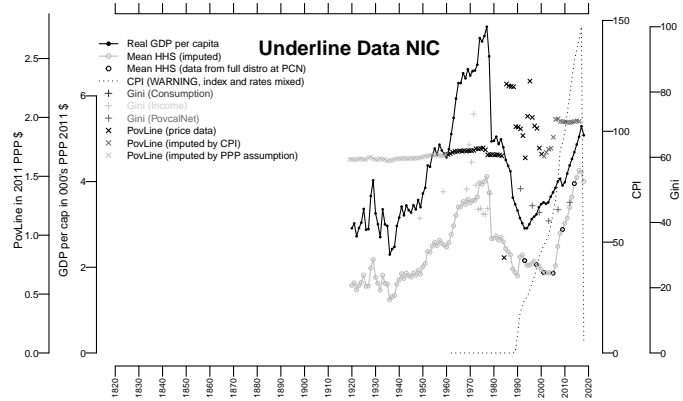
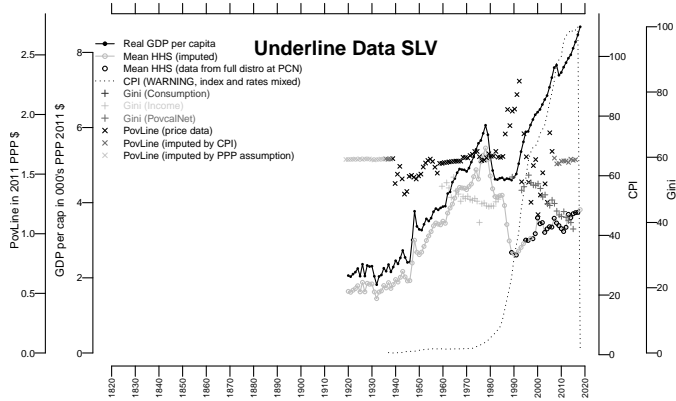
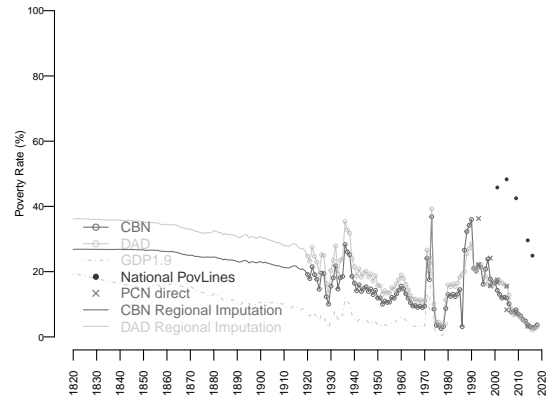
Poverty Rates in Paraguay – PRY – Latin America and Carib.



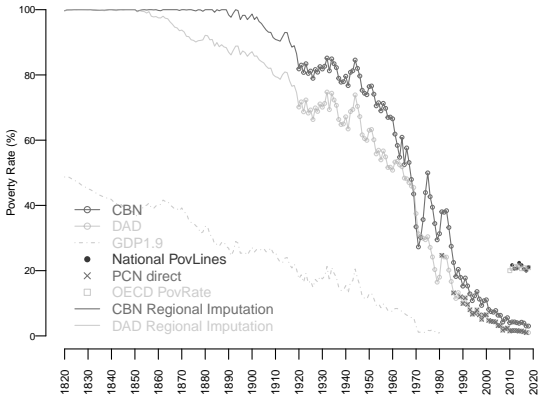
Poverty Rates in El Salvador – SLV – Latin America and Carib.



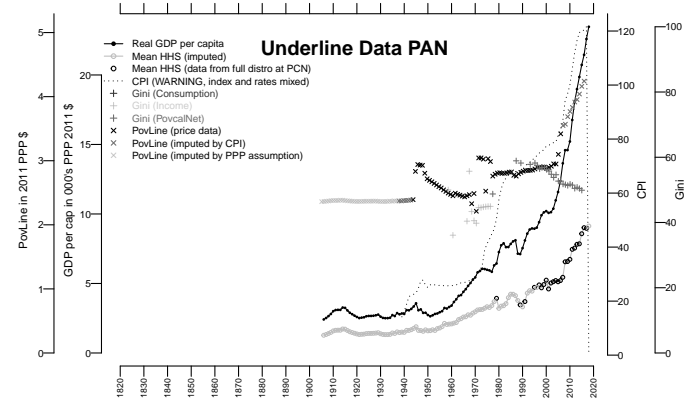
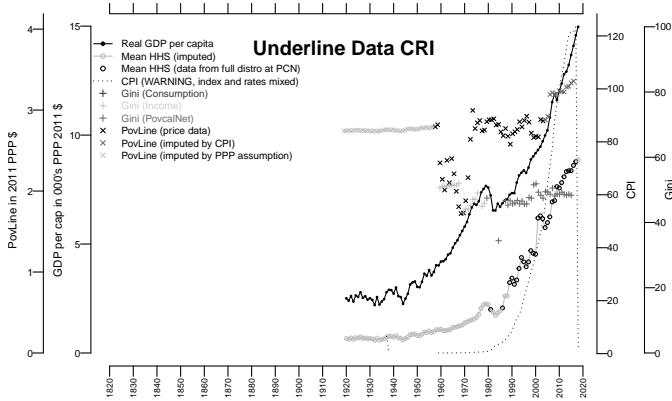
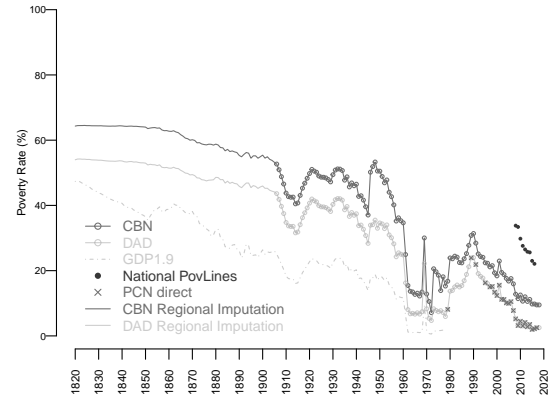
Poverty Rates in Nicaragua – NIC – Latin America and Carib.



### Poverty Rates in Costa Rica – CRI – Latin America and Carib.

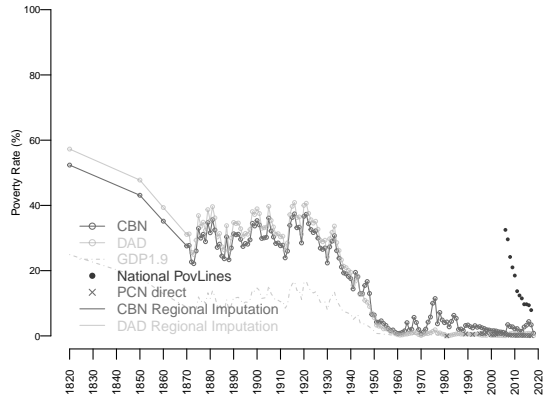


### Poverty Rates in Panama – PAN – Latin America and Carib.

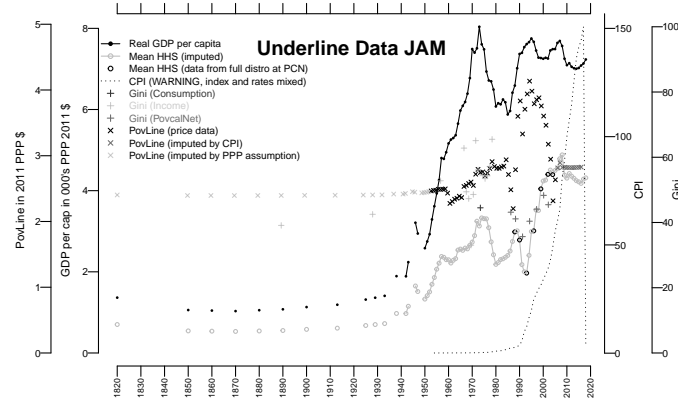
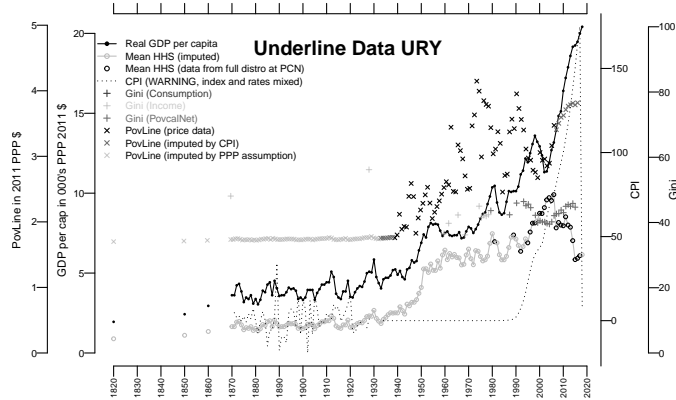
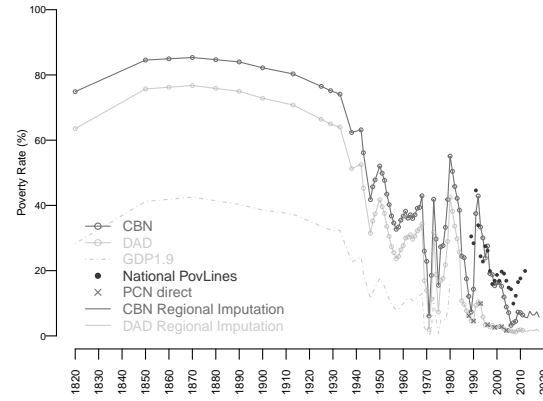




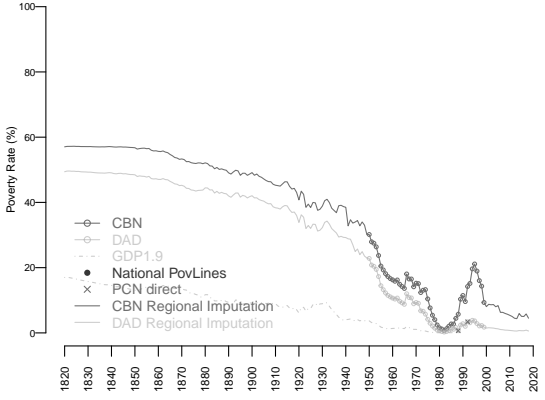
### Poverty Rates in Uruguay – URY – Latin America and Carib.



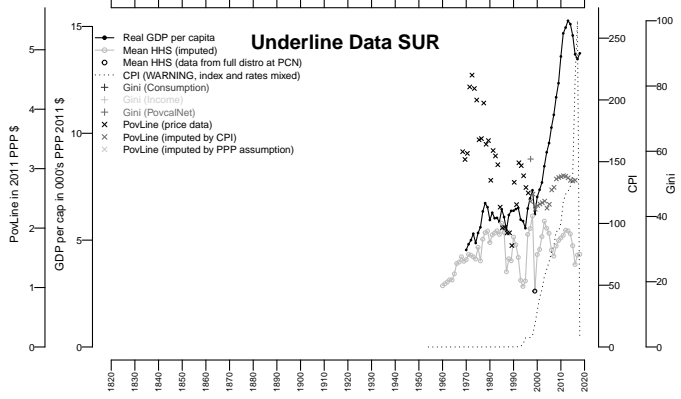
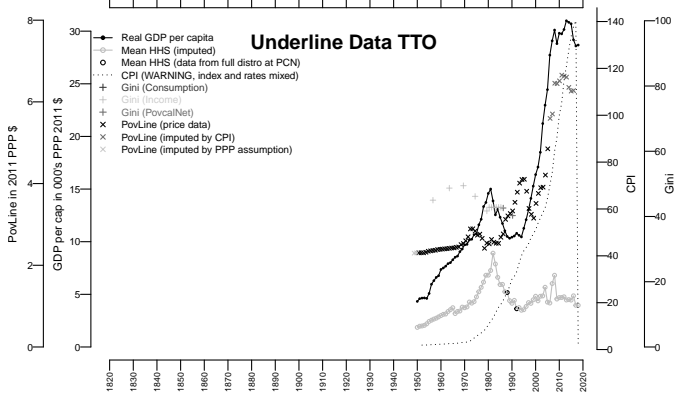
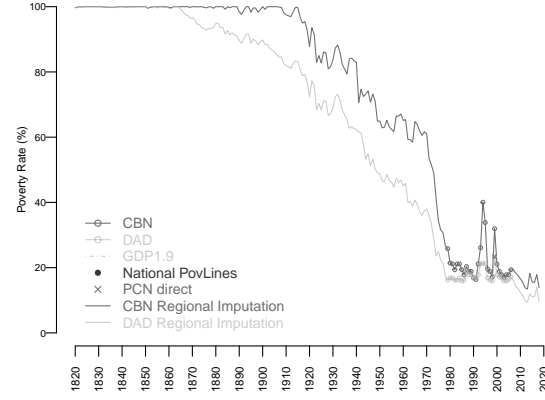
### Poverty Rates in Jamaica – JAM – Latin America and Carib.



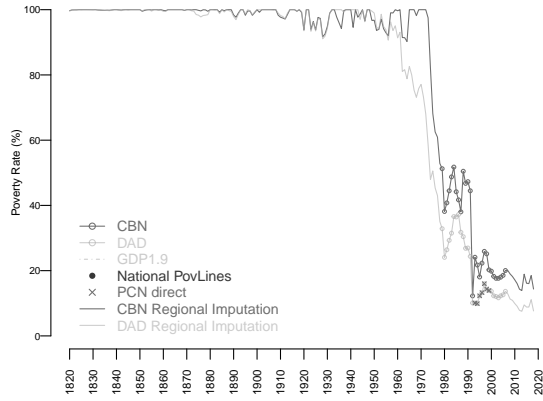
Poverty Rates in Trinidad and Tobago – TTO – Latin America and Carib.



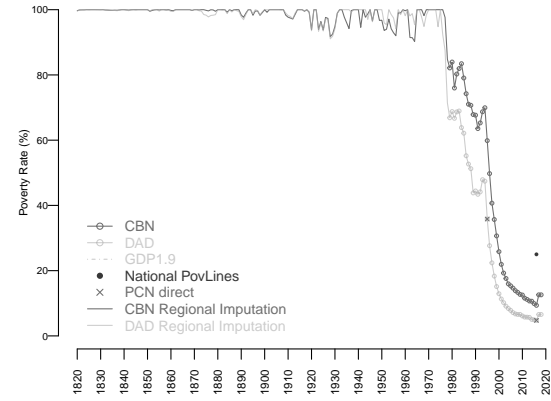
Poverty Rates in – SUR –



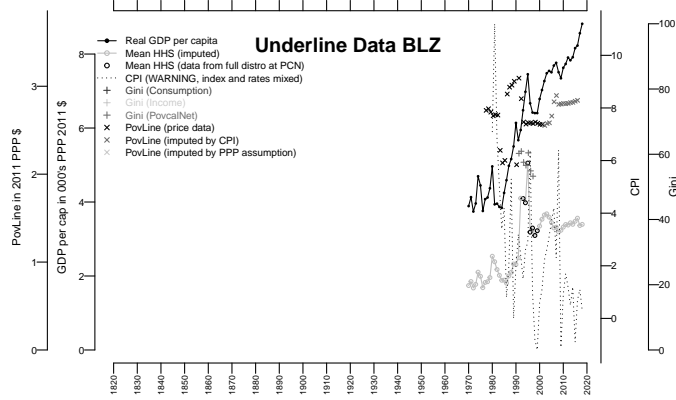
Poverty Rates in – BLZ –



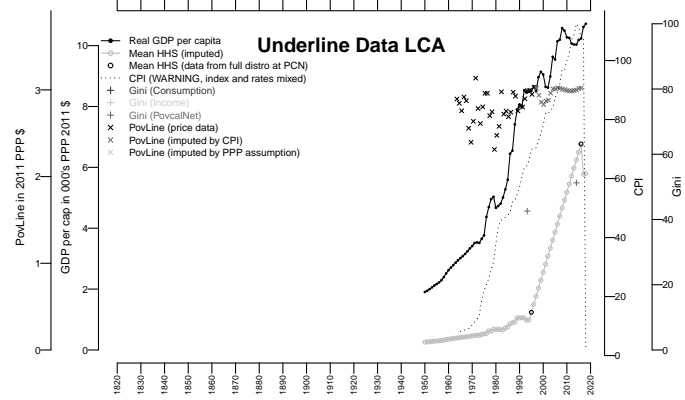
Poverty Rates in Saint Lucia – LCA – Latin America and Carib.



Underline Data BLZ

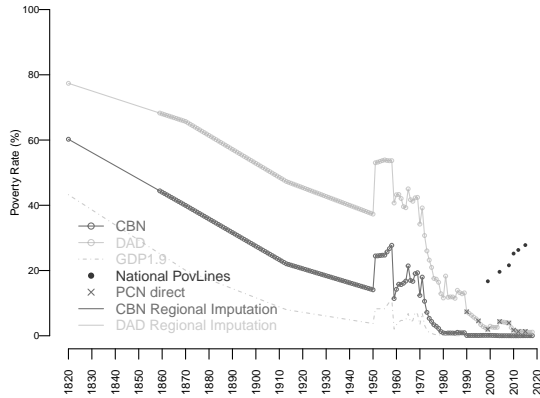


Underline Data LCA

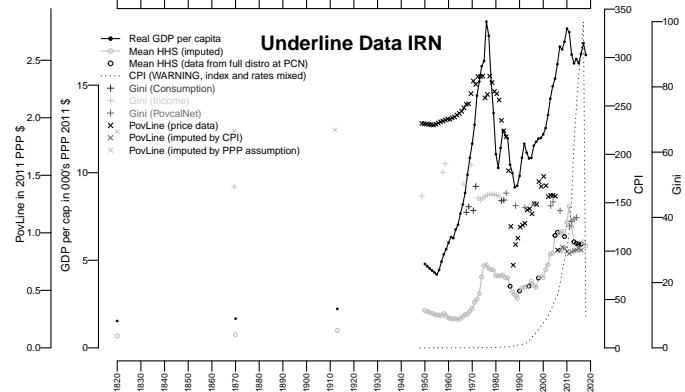
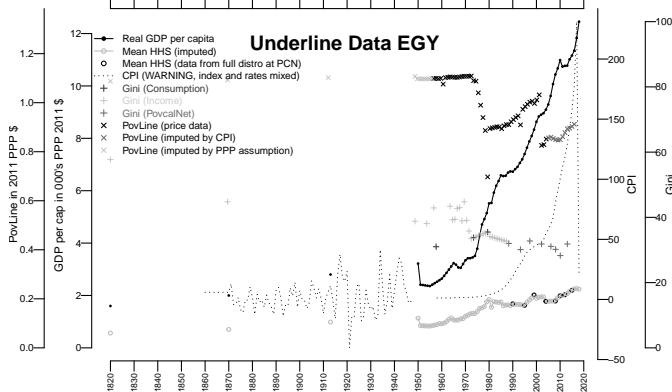
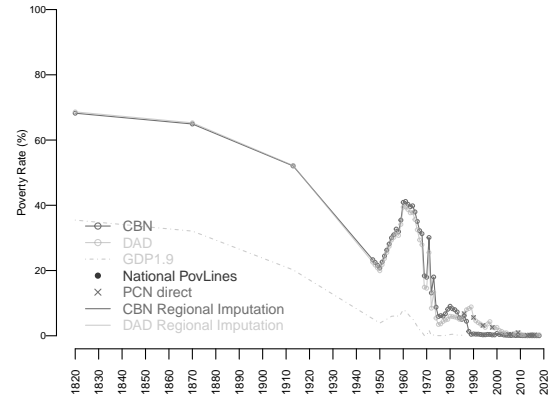


## 7.2.13 MENA

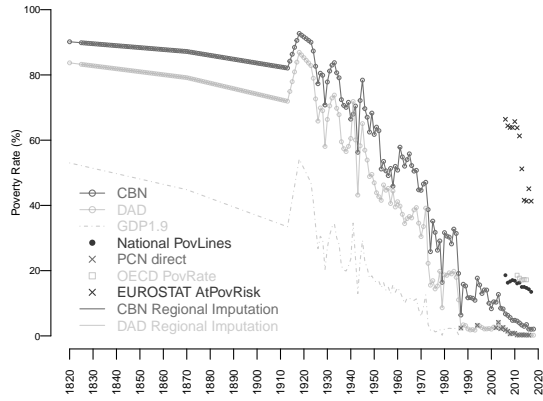
### Poverty Rates in Egypt – EGY – MENA



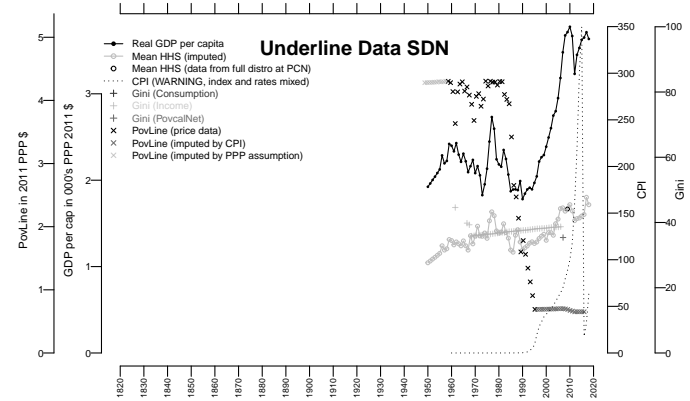
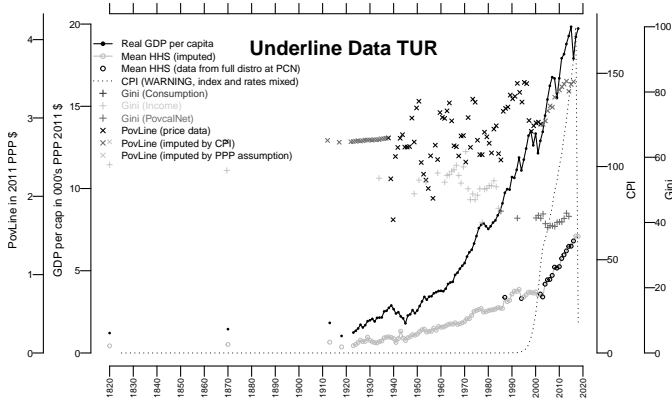
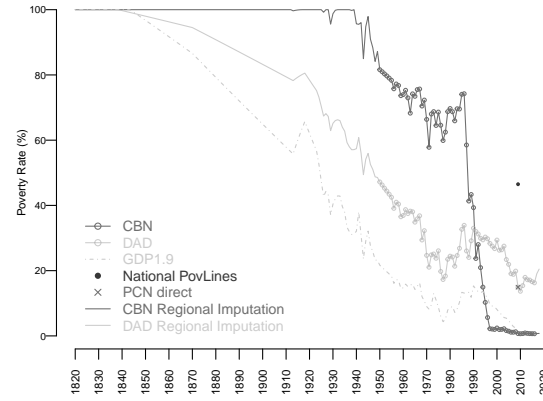
### Poverty Rates in Iran (Islamic Republic of) – IRN – MENA



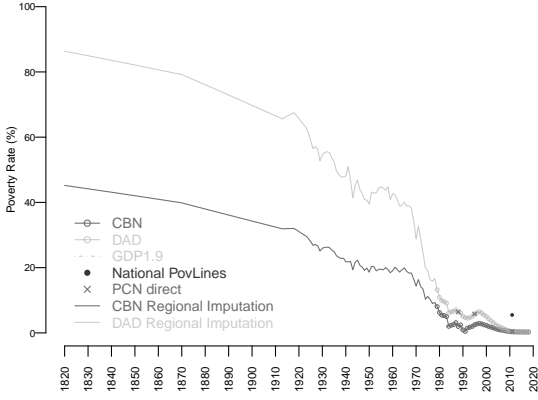
**Poverty Rates in Turkey – TUR – MENA**



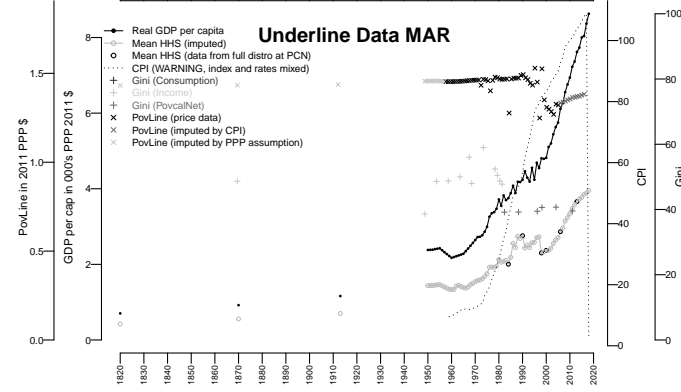
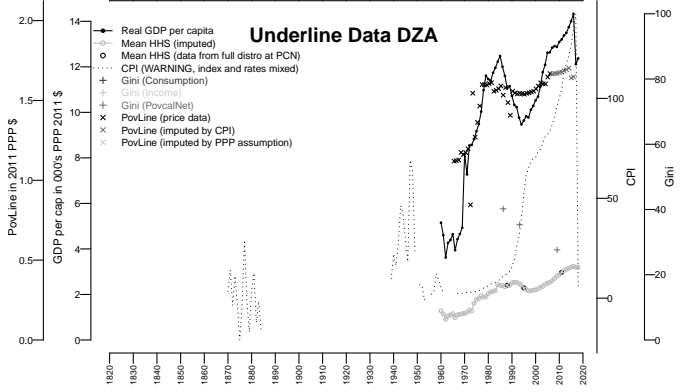
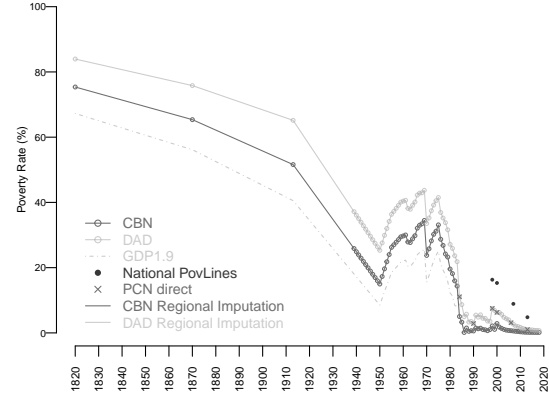
**Poverty Rates in Sudan (Former) – SDN – MENA**



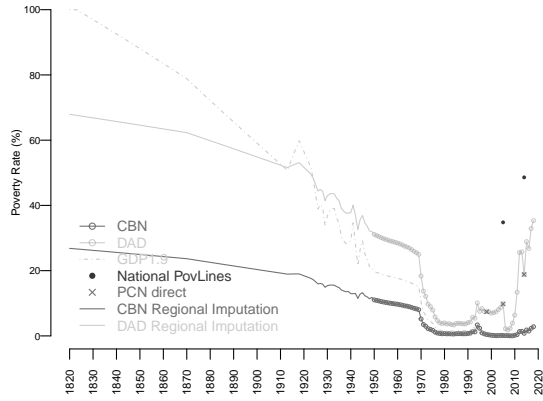
Poverty Rates in Algeria – DZA – MENA



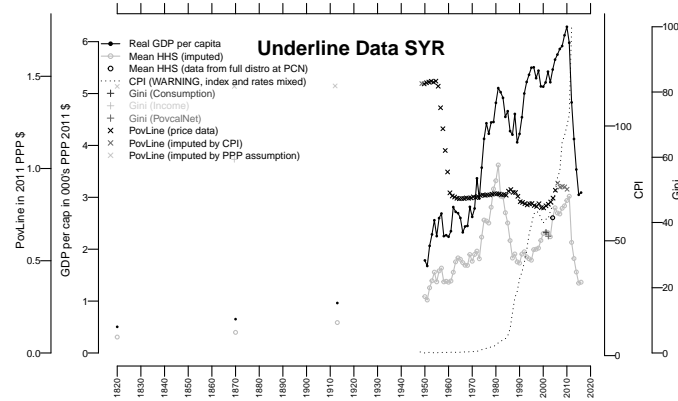
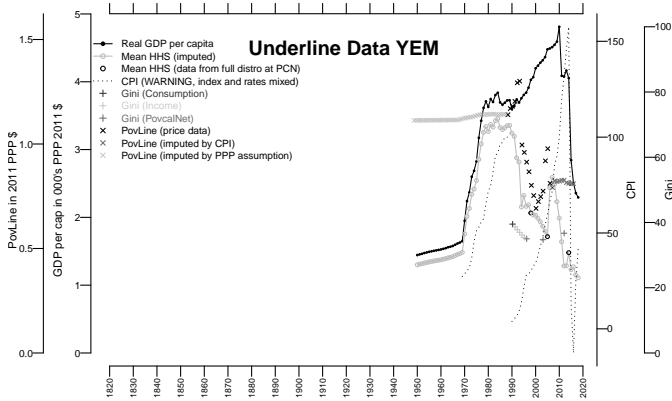
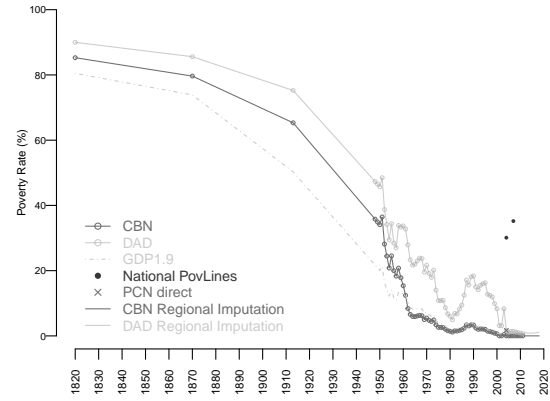
Poverty Rates in Morocco – MAR – MENA



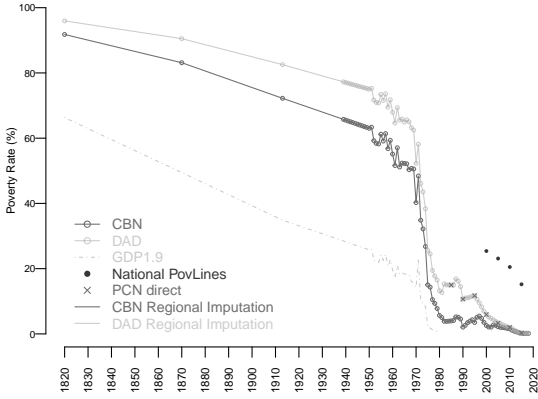
**Poverty Rates in Yemen – YEM – MENA**



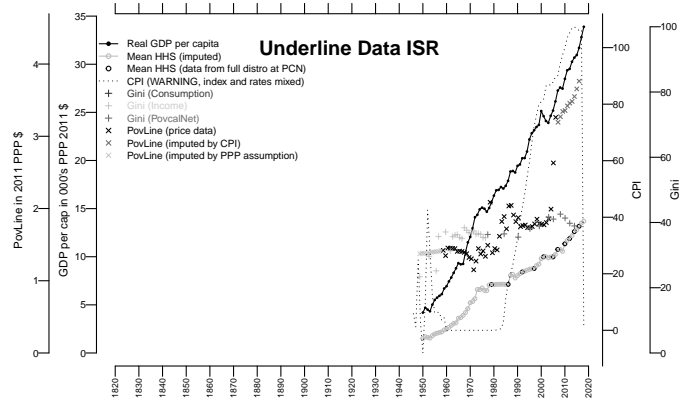
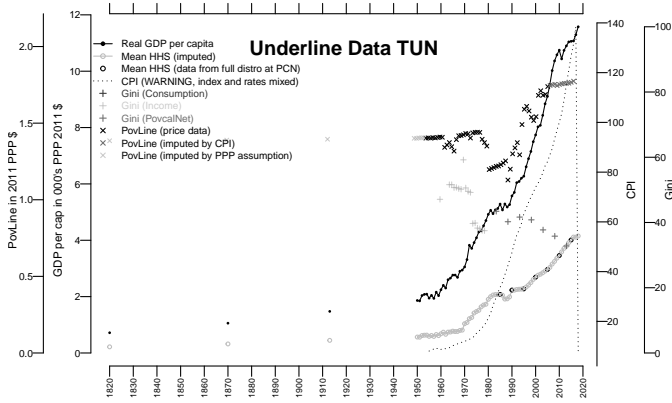
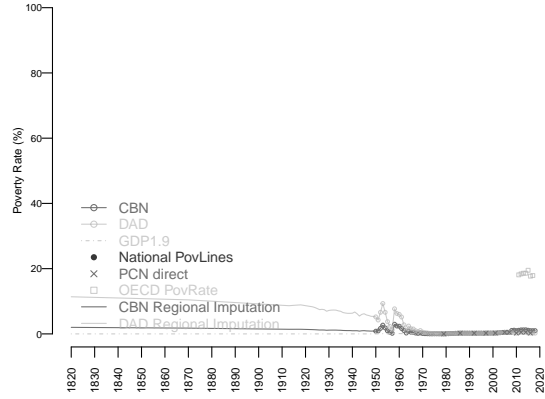
**Poverty Rates in Syrian Arab Republic – SYR – MENA**



Poverty Rates in Tunisia – TUN – MENA

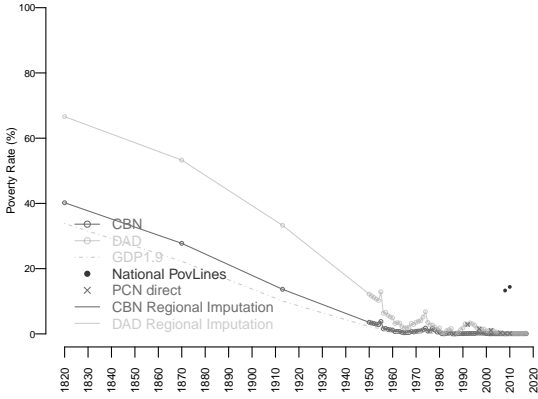


Poverty Rates in Israel – ISR – MENA

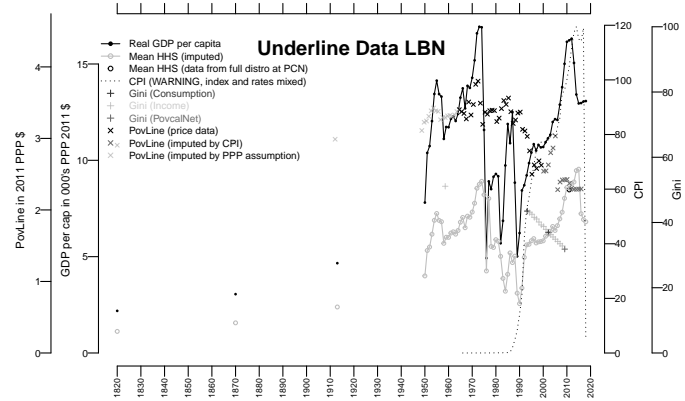
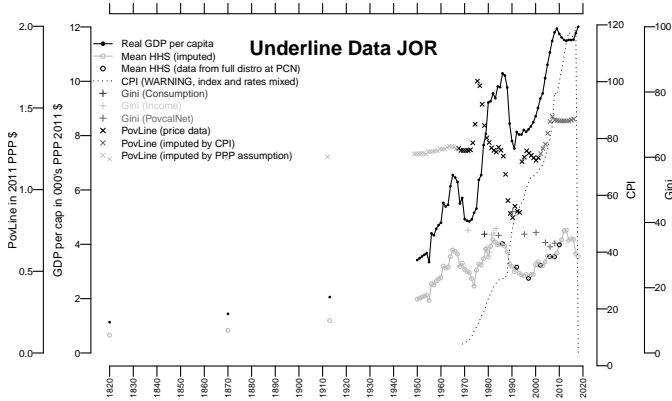
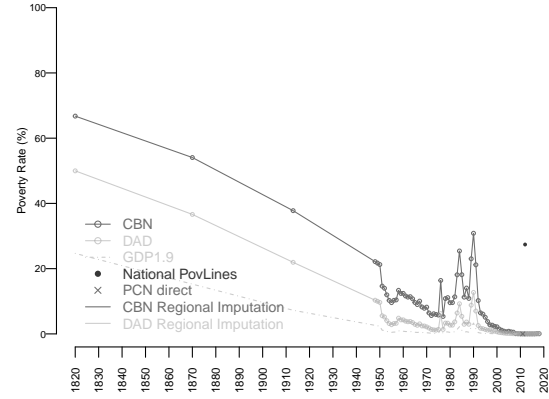




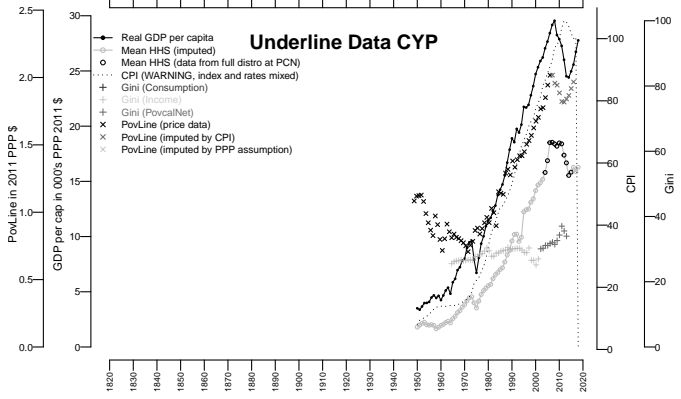
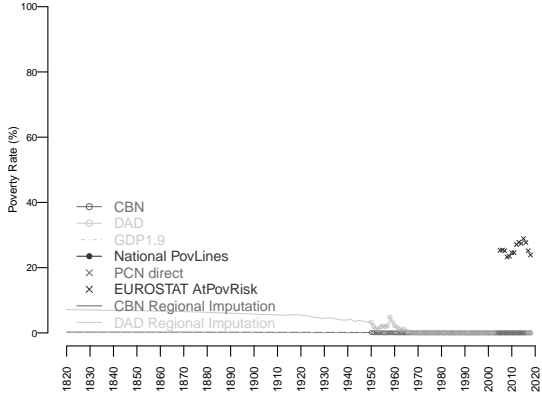
Poverty Rates in Jordan – JOR – MENA



Poverty Rates in Lebanon – LBN – MENA

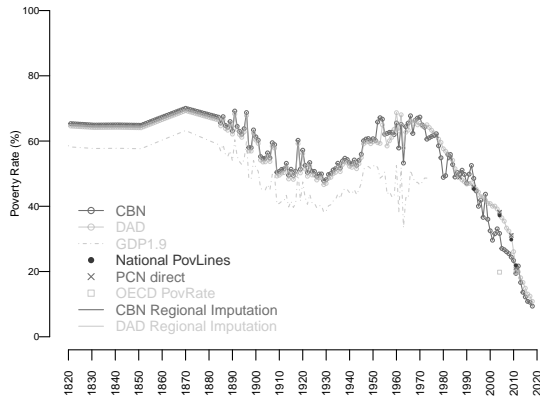


### Poverty Rates in Cyprus – CYP – MENA

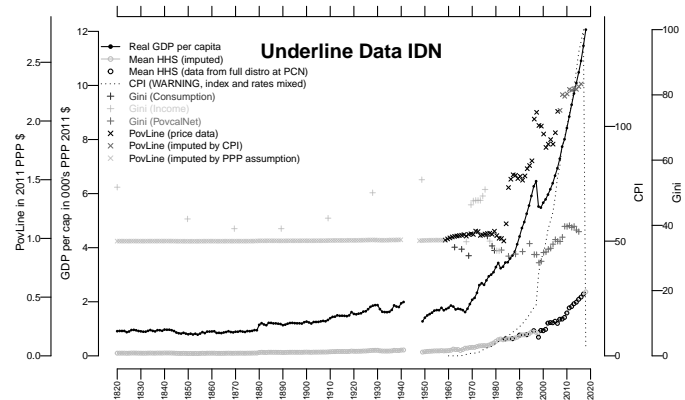
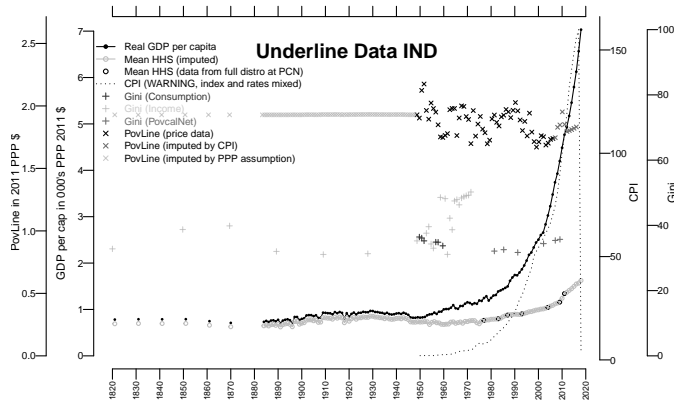
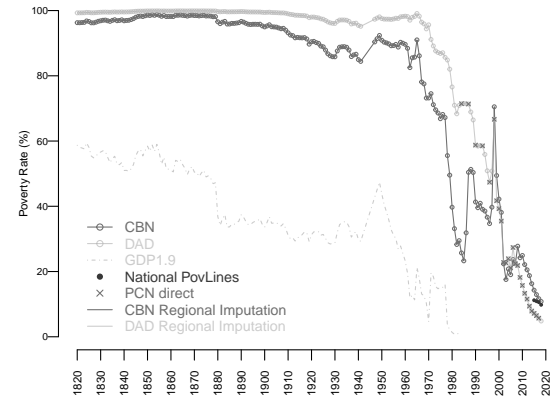


## 7.2.14 South and South-East Asia

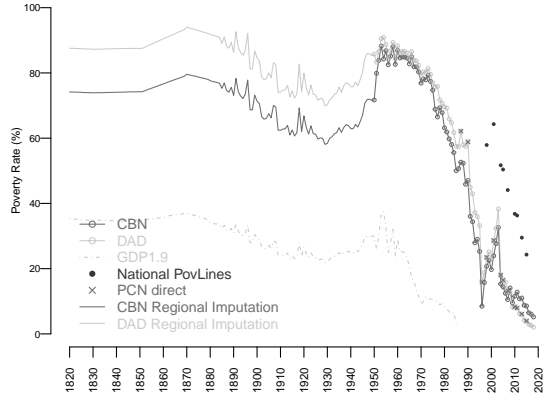
Poverty Rates in India – IND – South and South-East Asia



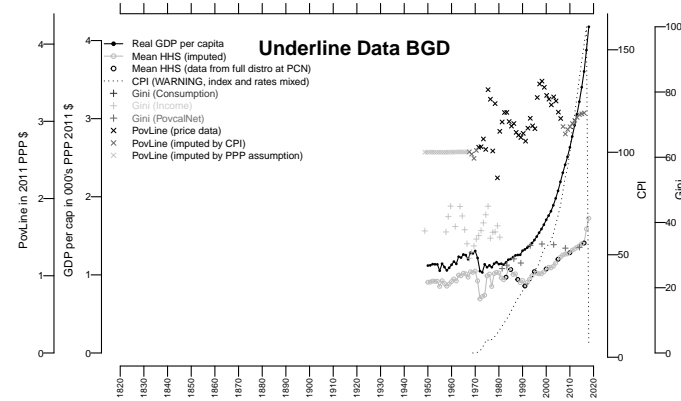
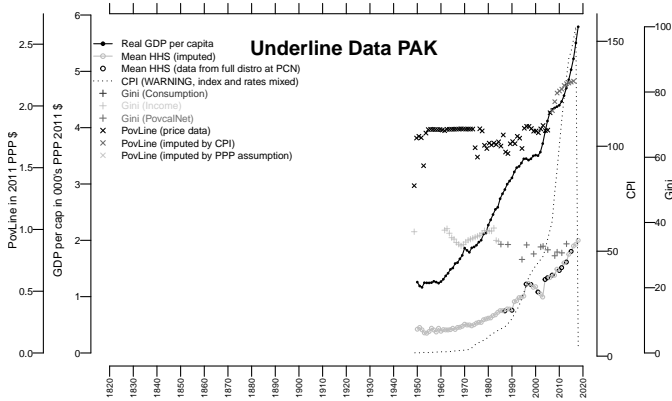
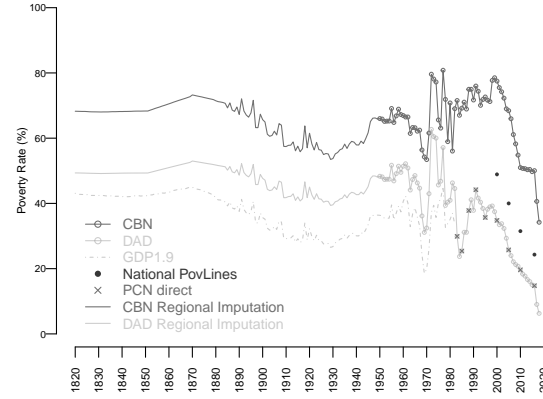
Poverty Rates in Indonesia – IDN – South and South-East Asia



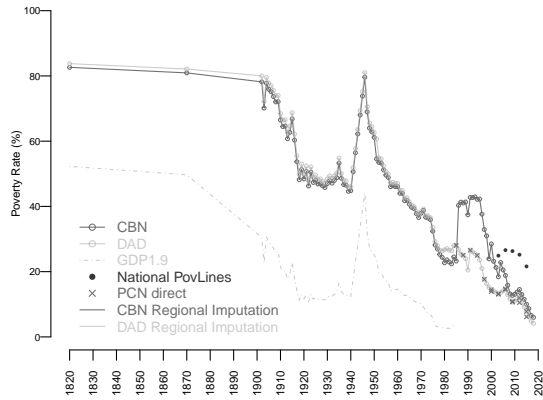
**Poverty Rates in Pakistan – PAK – South and South–East Asia**



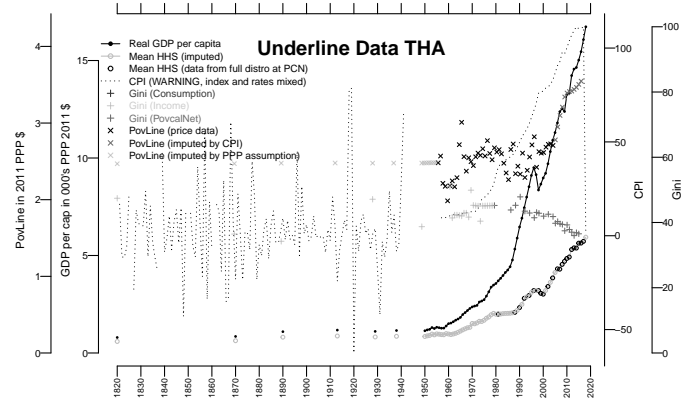
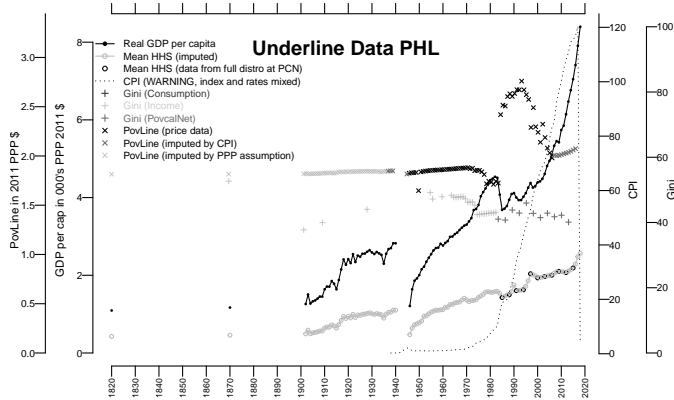
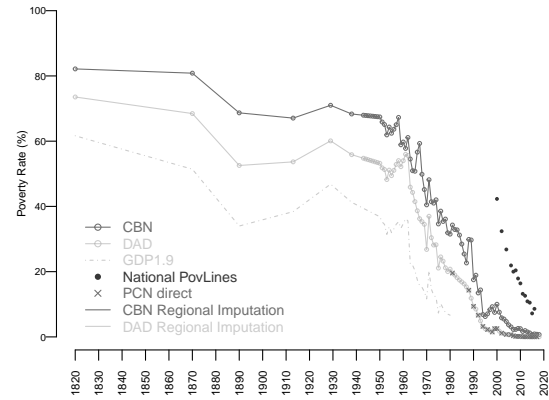
**Poverty Rates in Bangladesh – BGD – South and South–East Asia**



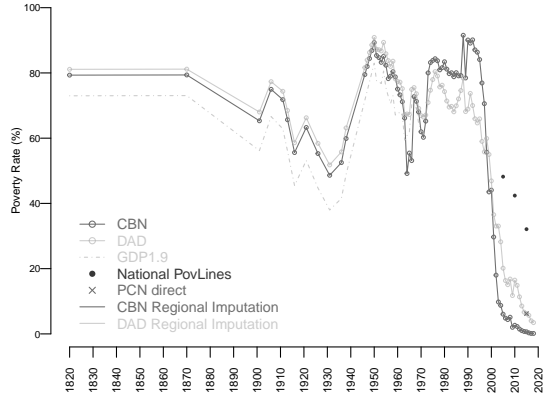
### Poverty Rates in Philippines – PHL – South and South-East Asia



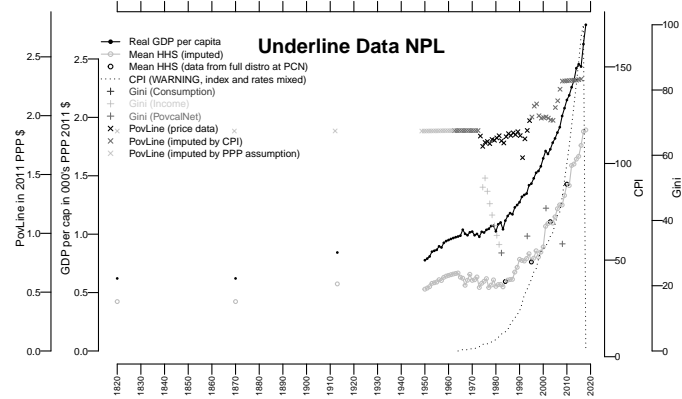
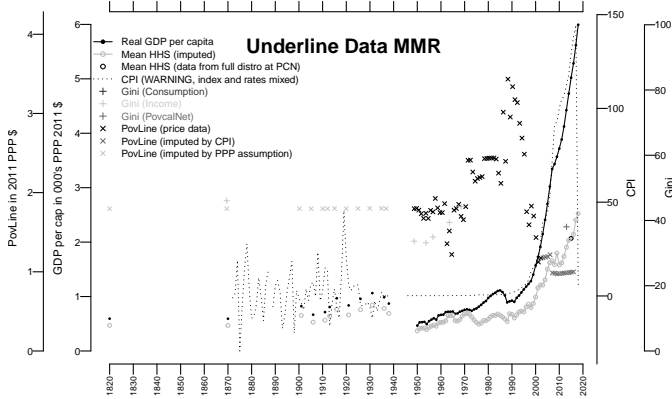
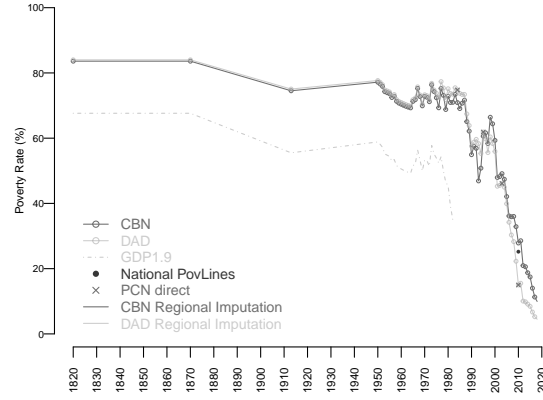
### Poverty Rates in Thailand – THA – South and South-East Asia



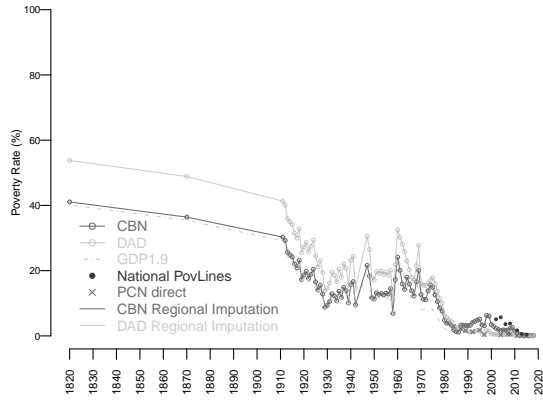
### Poverty Rates in Myanmar – MMR – South and South–East Asia



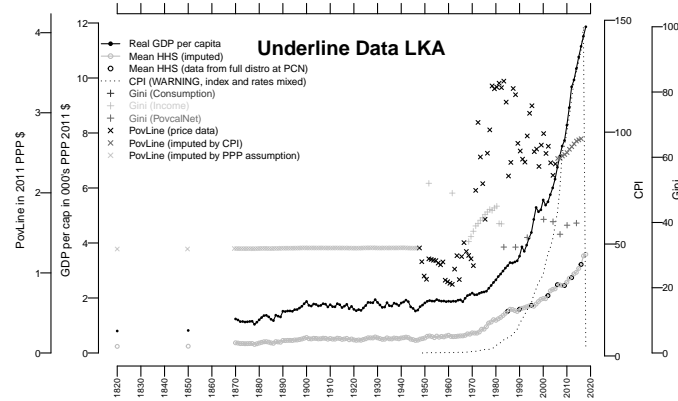
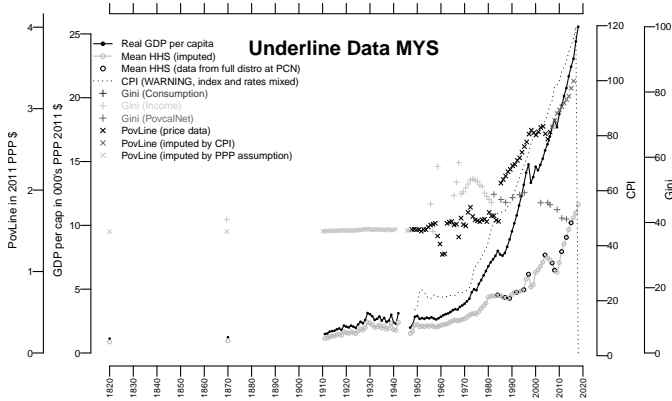
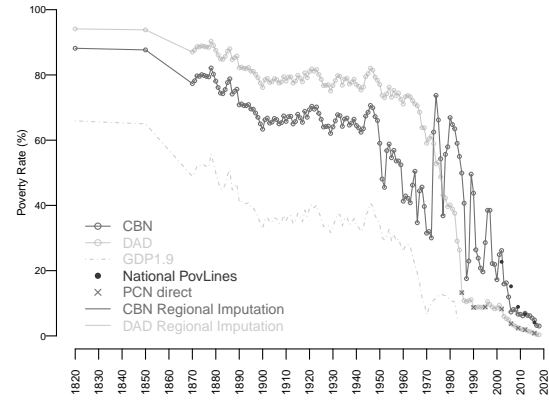
### Poverty Rates in Nepal – NPL – South and South–East Asia



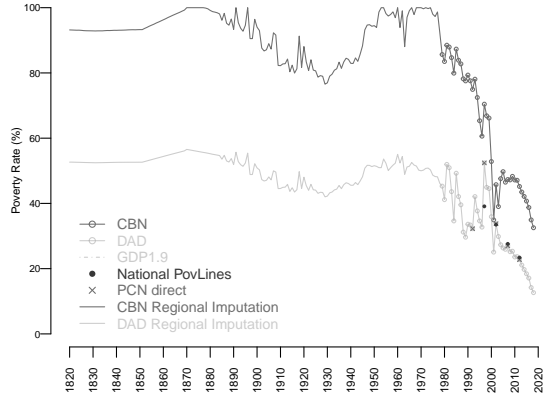
### Poverty Rates in Malaysia – MYS – South and South–East Asia



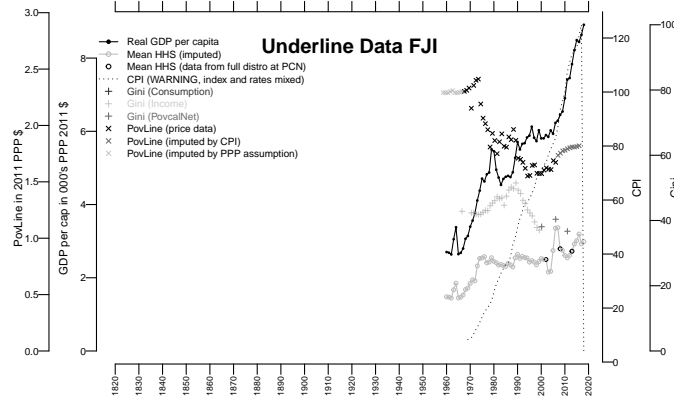
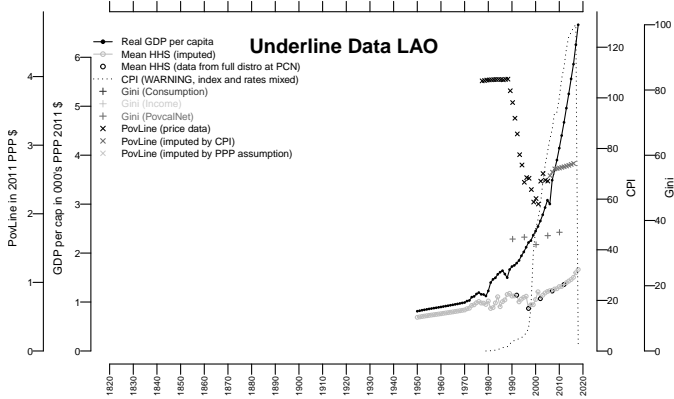
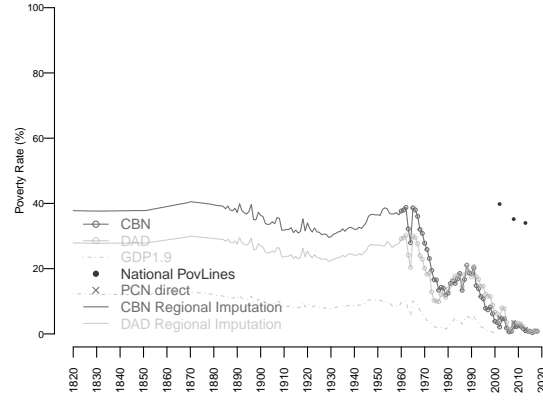
### Poverty Rates in Sri Lanka – LKA – South and South–East Asia



### Poverty Rates in Lao People's DR – LAO – South and South-East Asia

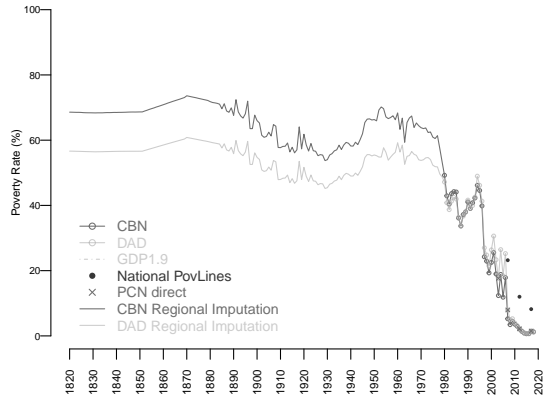


### Poverty Rates in – FJI –

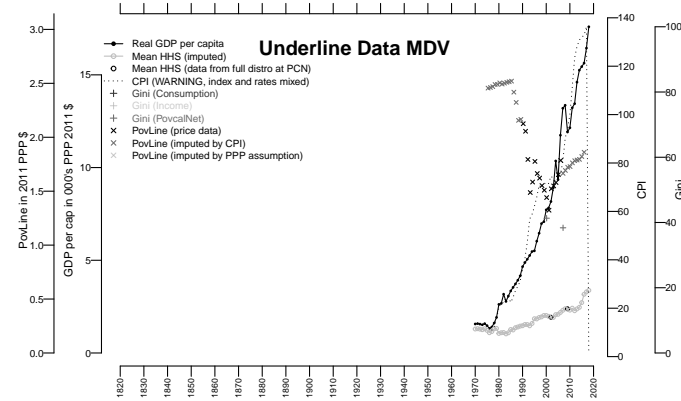
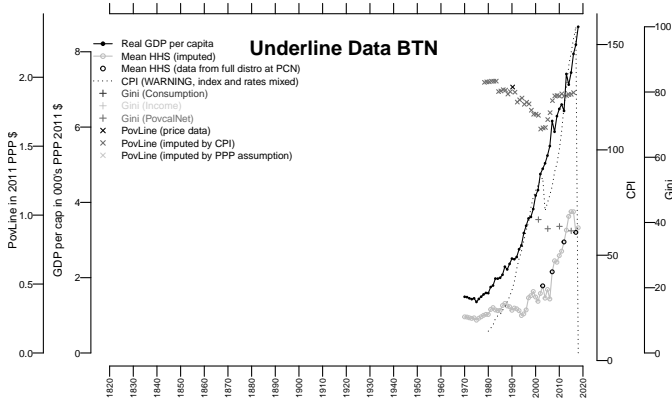
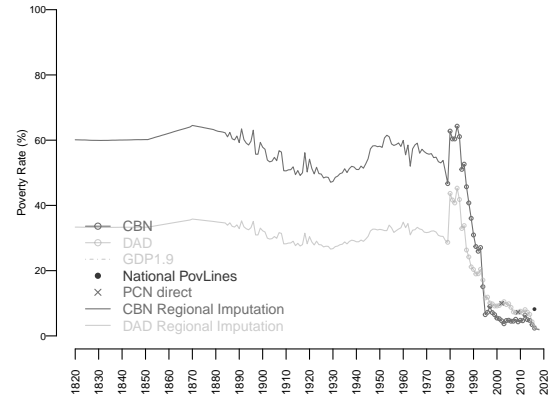




Poverty Rates in – BTN –

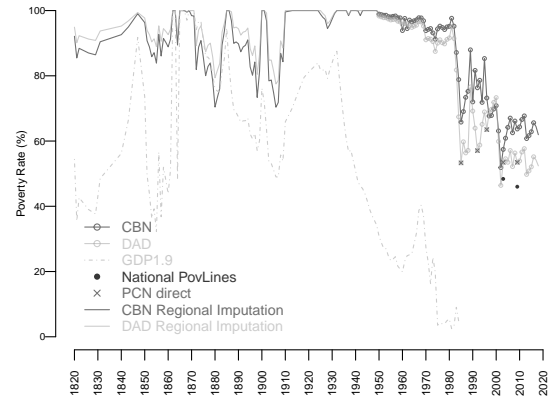


Poverty Rates in – MDV –

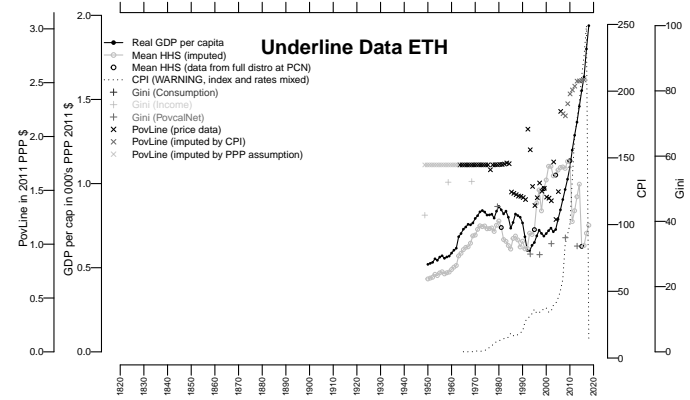
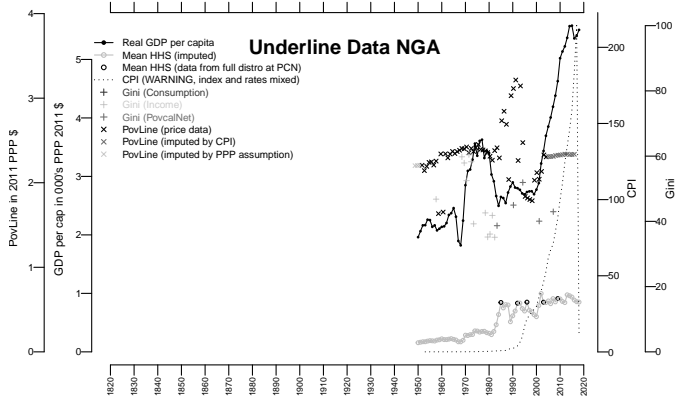
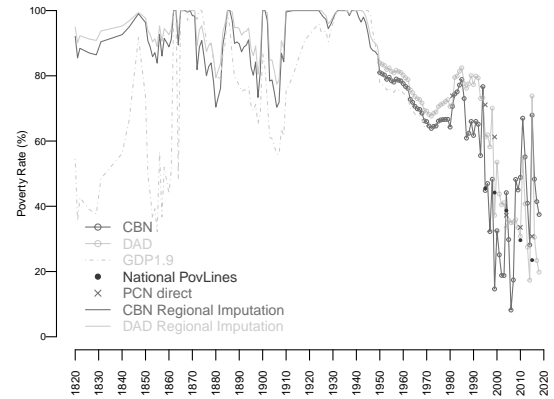


### 7.2.15 Sub-Saharan Africa

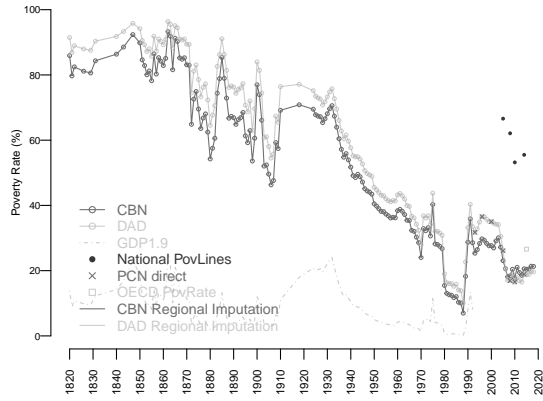
Poverty Rates in Nigeria – NGA – Sub-Saharan Africa



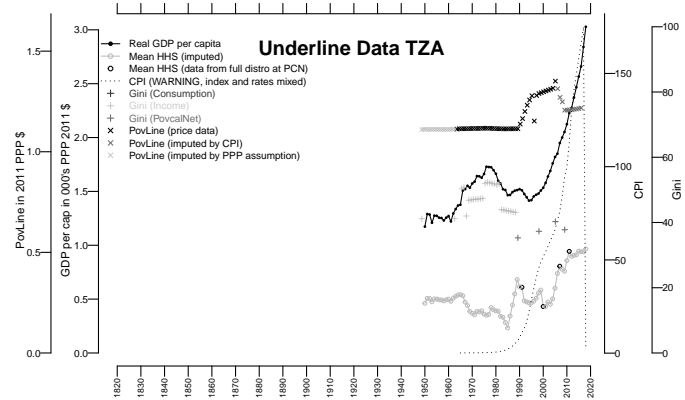
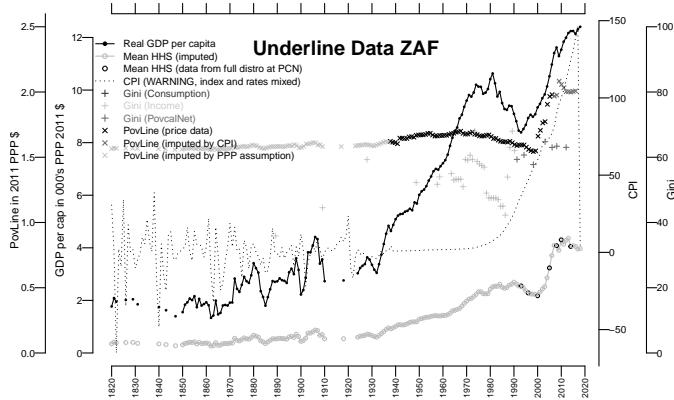
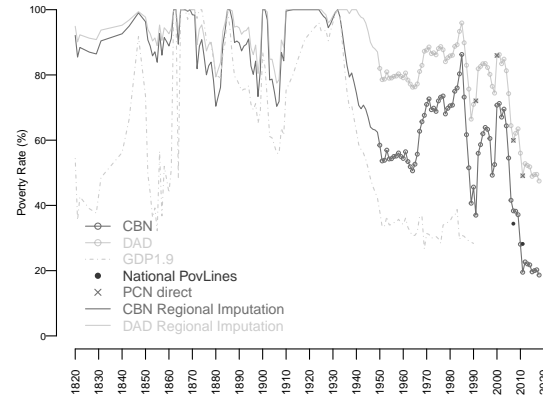
Poverty Rates in Ethiopia – ETH – Sub-Saharan Africa



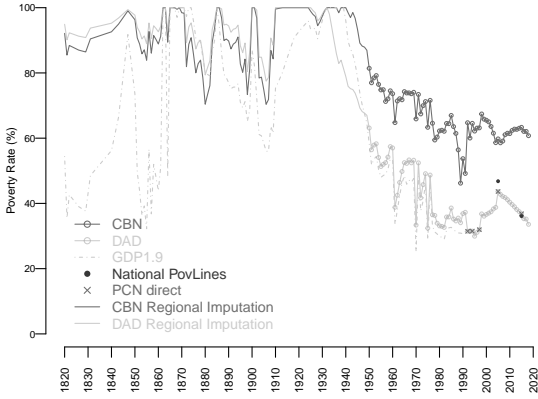
### Poverty Rates in South Africa – ZAF – Sub-Saharan Africa



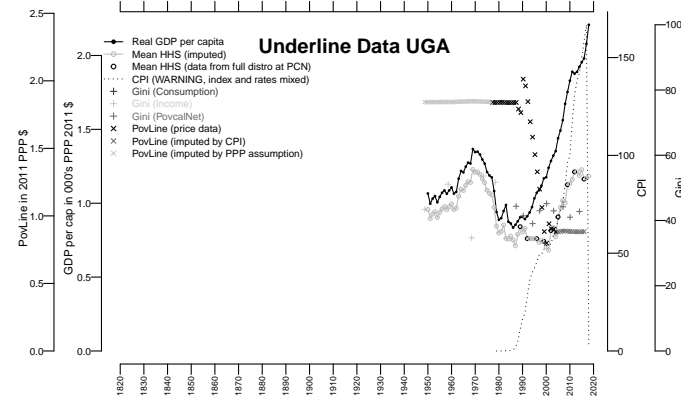
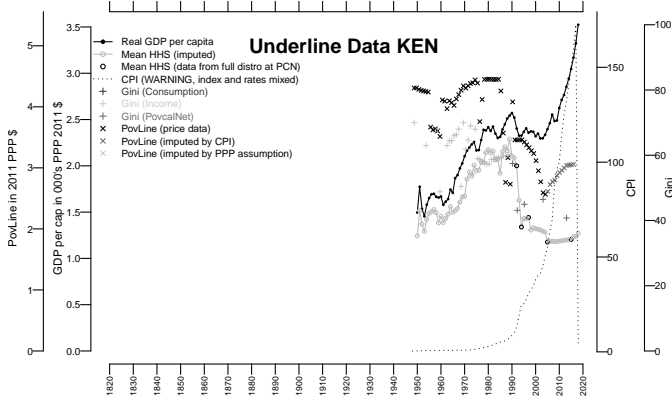
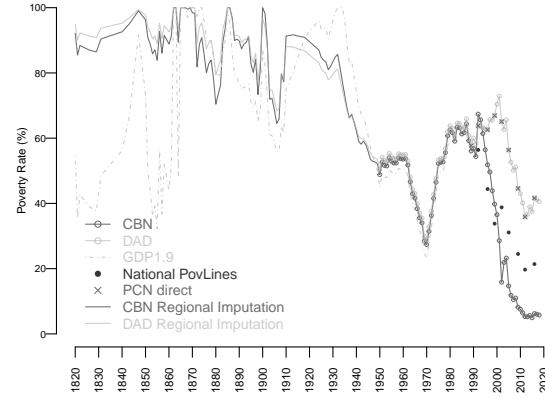
### Poverty Rates in U.R. of Tanzania: Mainland – TZA – Sub-Saharan Africa



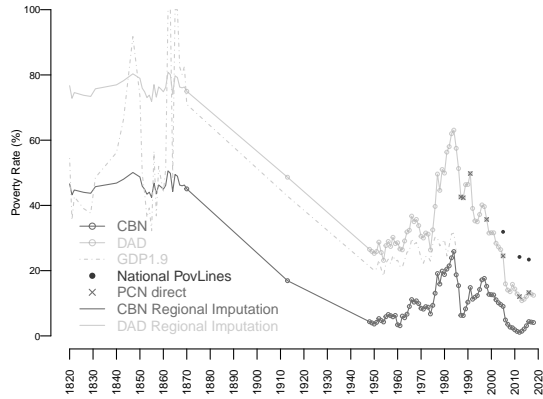
**Poverty Rates in Kenya – KEN – Sub-Saharan Africa**



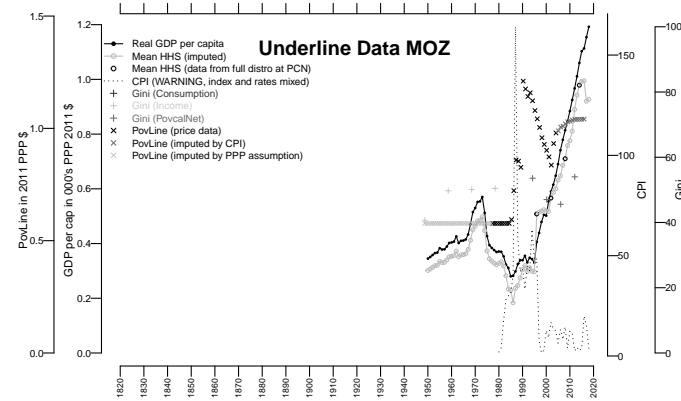
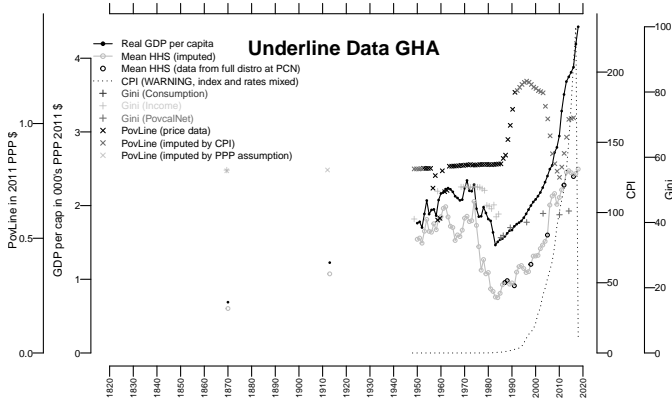
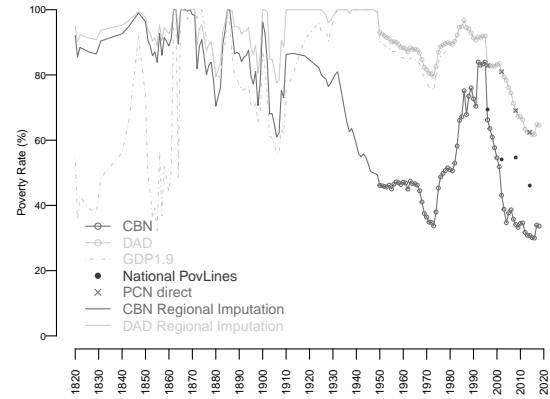
**Poverty Rates in Uganda – UGA – Sub-Saharan Africa**



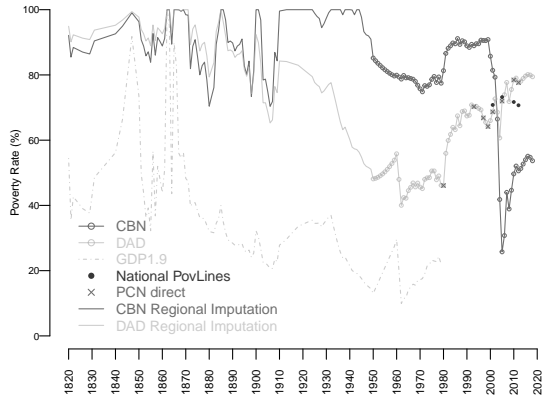
Poverty Rates in Ghana – GHA – Sub-Saharan Africa



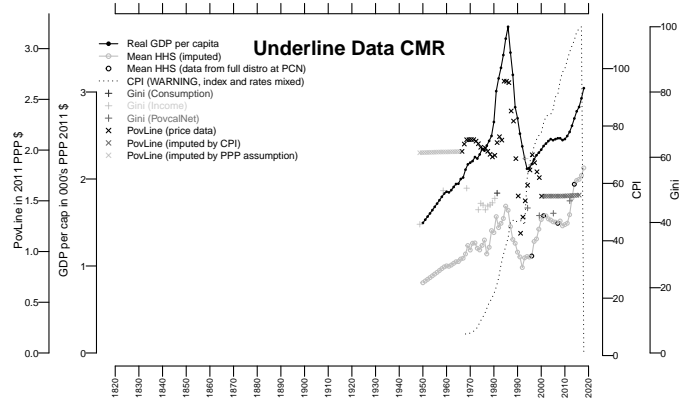
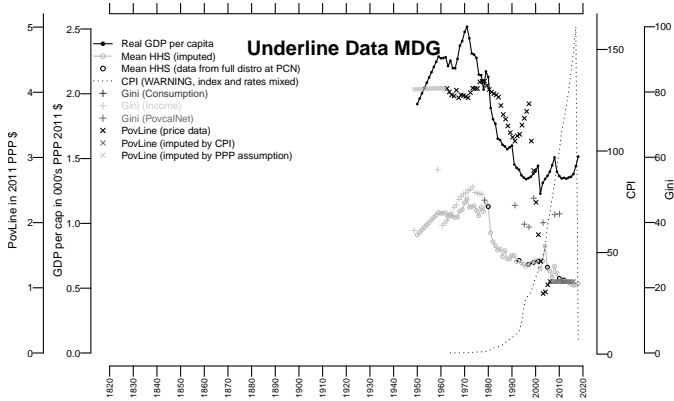
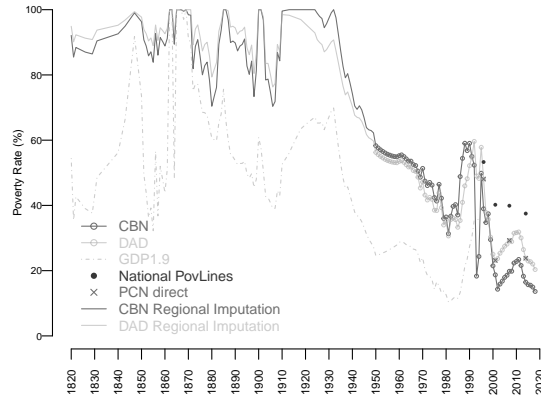
Poverty Rates in Mozambique – MOZ – Sub-Saharan Africa



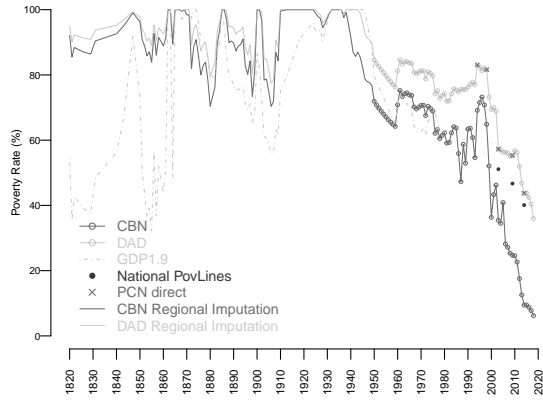
**Poverty Rates in Madagascar – MDG – Sub-Saharan Africa**



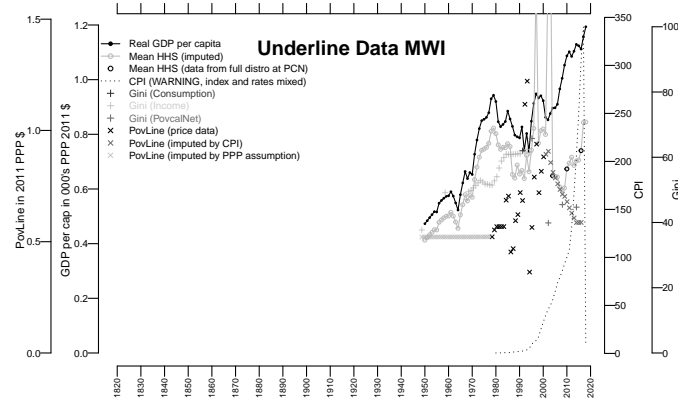
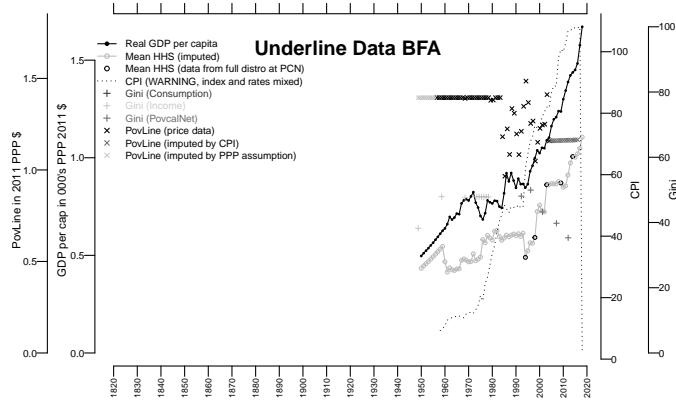
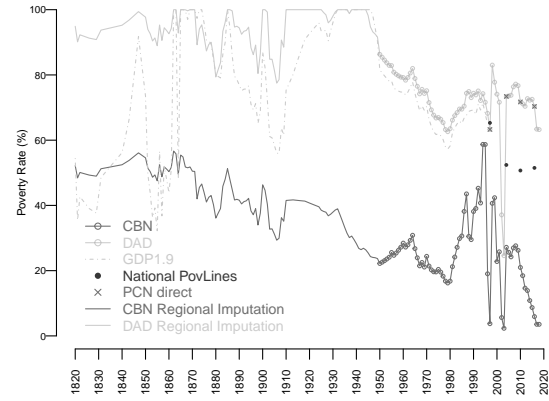
**Poverty Rates in Cameroon – CMR – Sub-Saharan Africa**



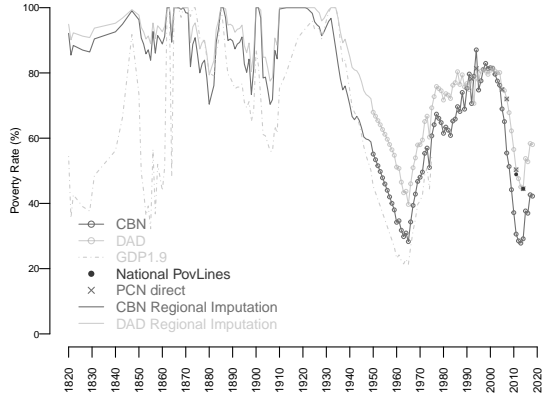
### Poverty Rates in Burkina Faso – BFA – Sub-Saharan Africa



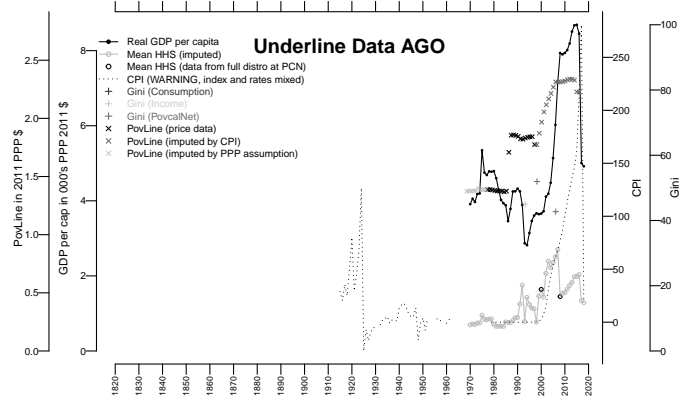
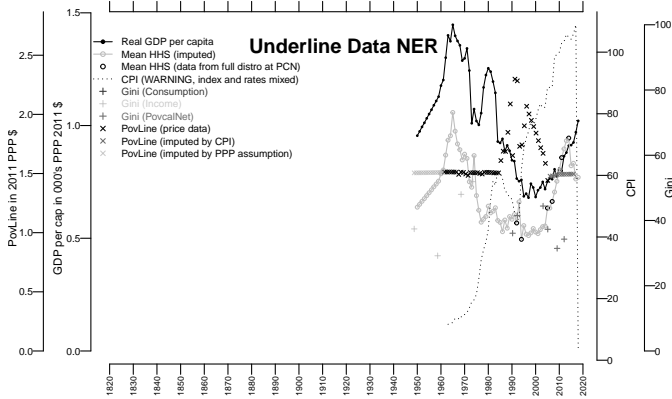
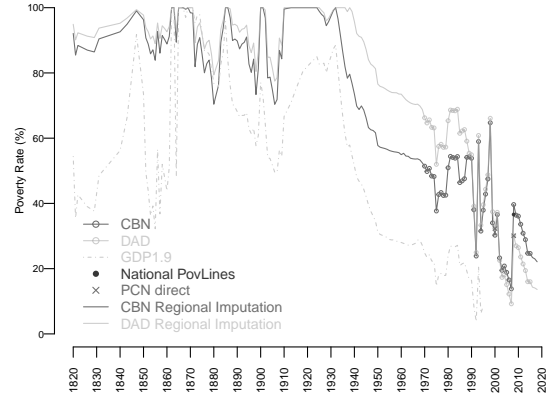
### Poverty Rates in Malawi – MWI – Sub-Saharan Africa



**Poverty Rates in Niger – NER – Sub-Saharan Africa**

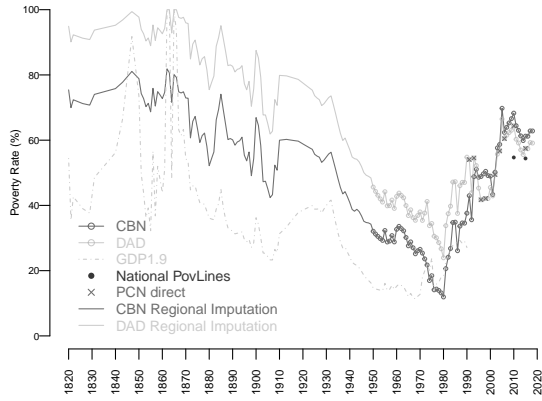


**Poverty Rates in Angola – AGO – Sub-Saharan Africa**

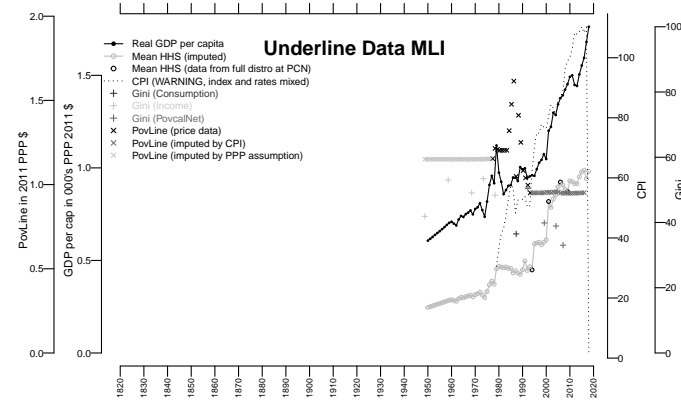
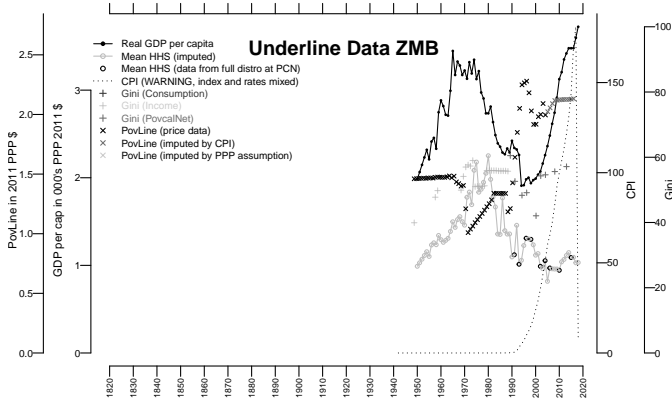
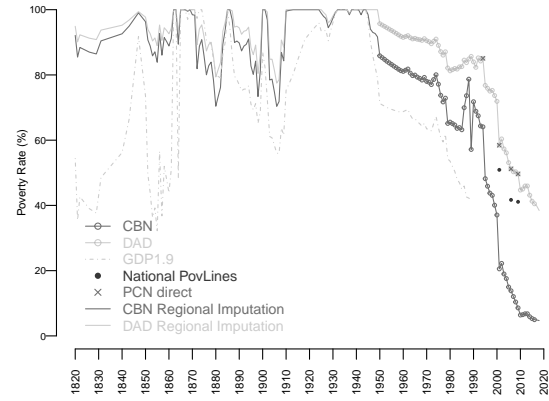




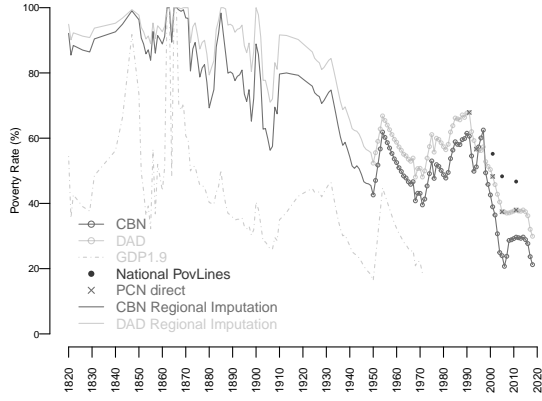
### Poverty Rates in Zambia – ZMB – Sub-Saharan Africa



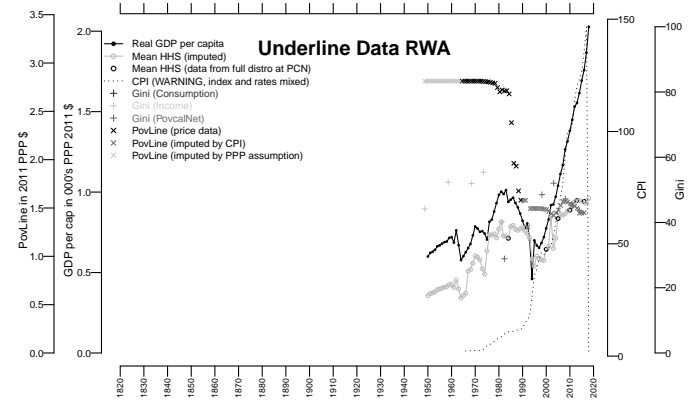
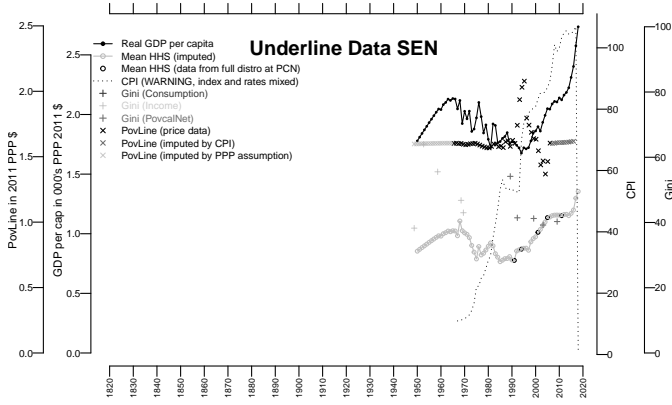
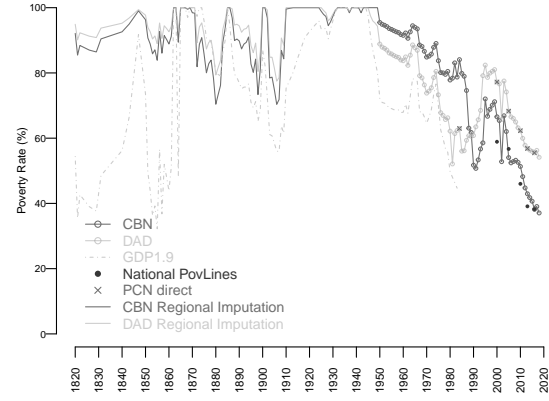
### Poverty Rates in Mali – MLI – Sub-Saharan Africa



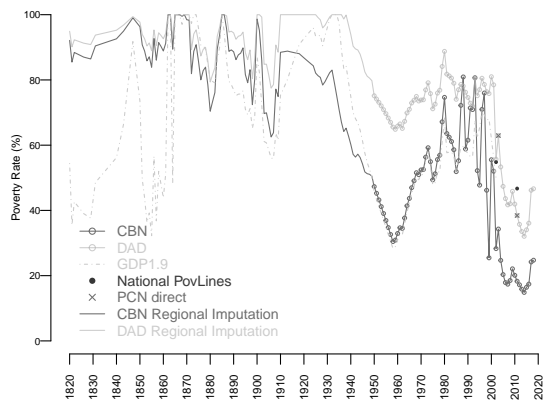
**Poverty Rates in Senegal – SEN – Sub-Saharan Africa**



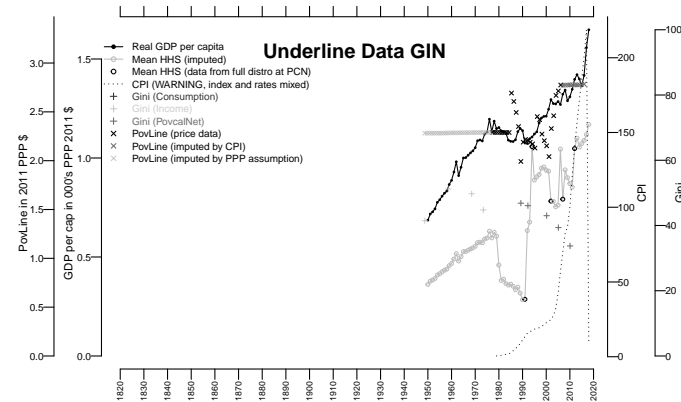
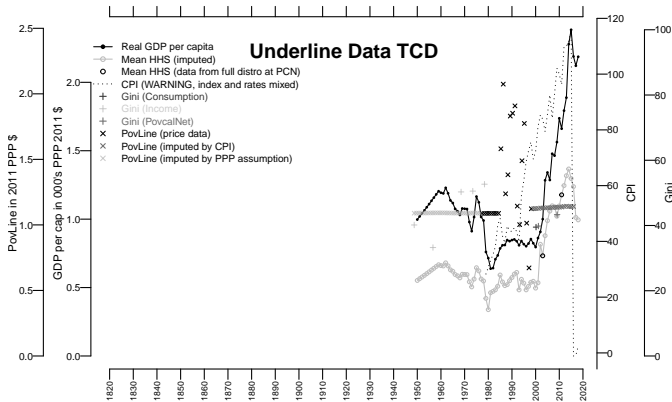
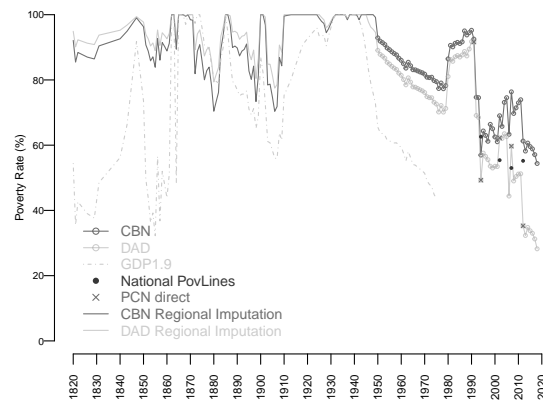
**Poverty Rates in Rwanda – RWA – Sub-Saharan Africa**



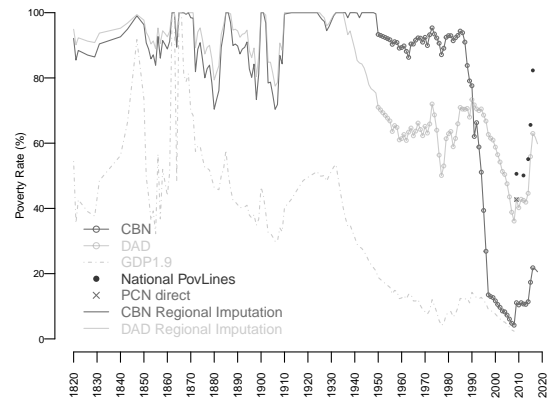
**Poverty Rates in Chad – TCD – Sub-Saharan Africa**



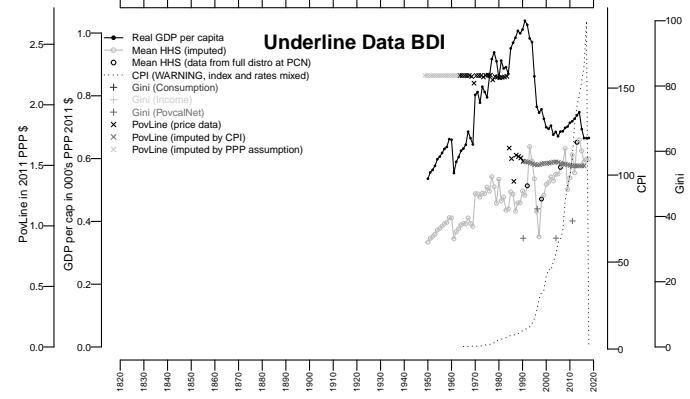
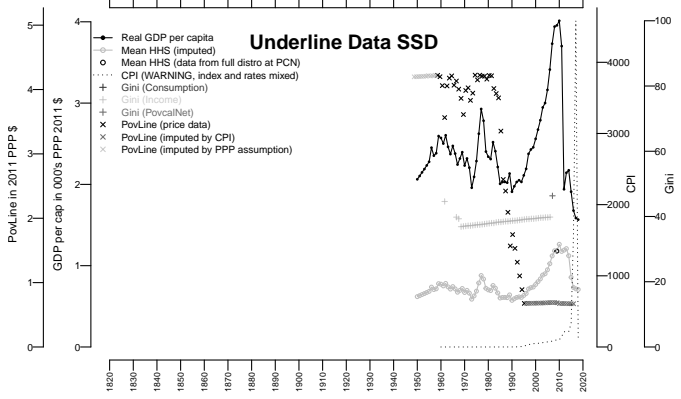
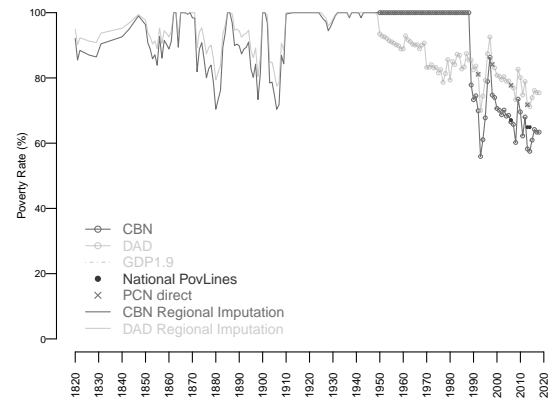
**Poverty Rates in Guinea – GIN – Sub-Saharan Africa**



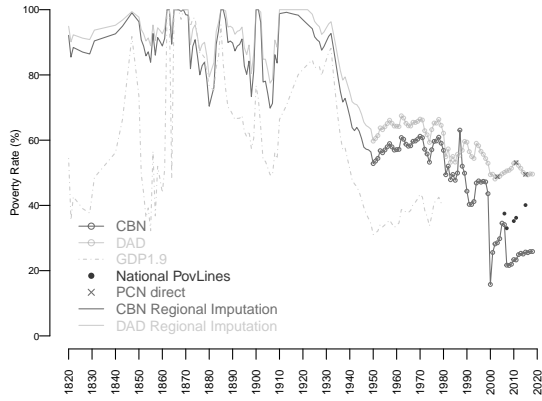
Poverty Rates in – SSD –



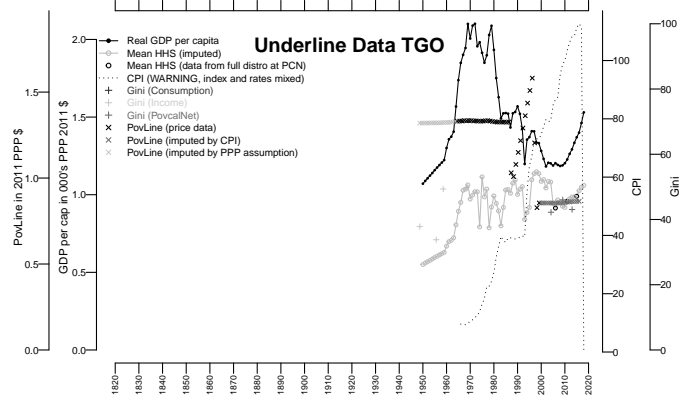
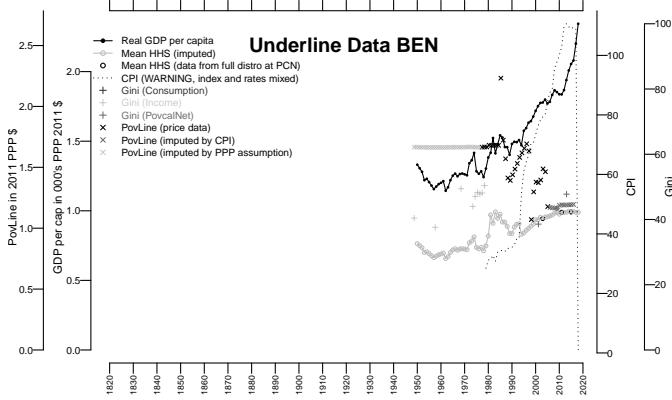
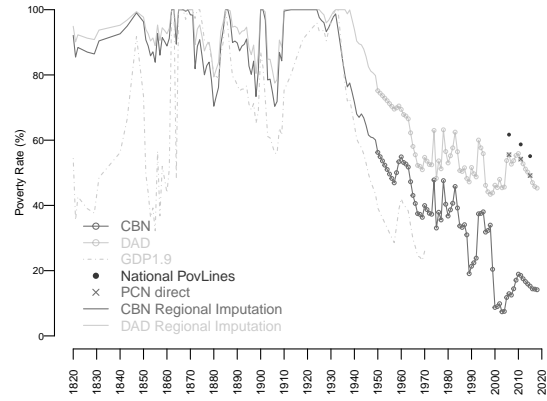
Poverty Rates in Burundi – BDI – Sub-Saharan Africa



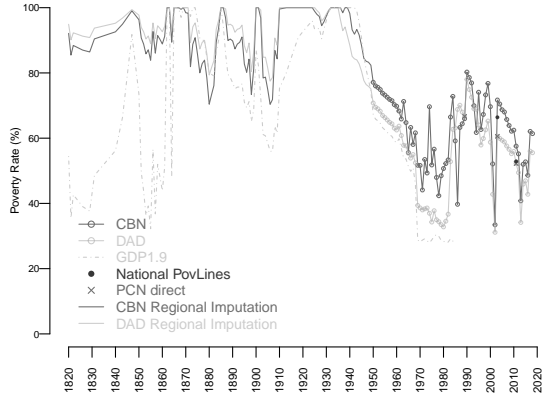
**Poverty Rates in Benin – BEN – Sub-Saharan Africa**



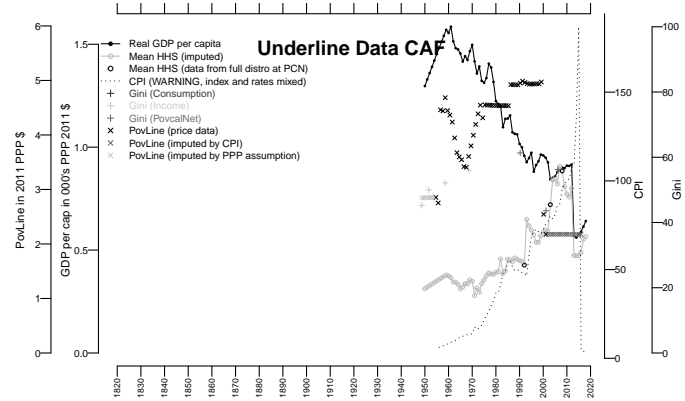
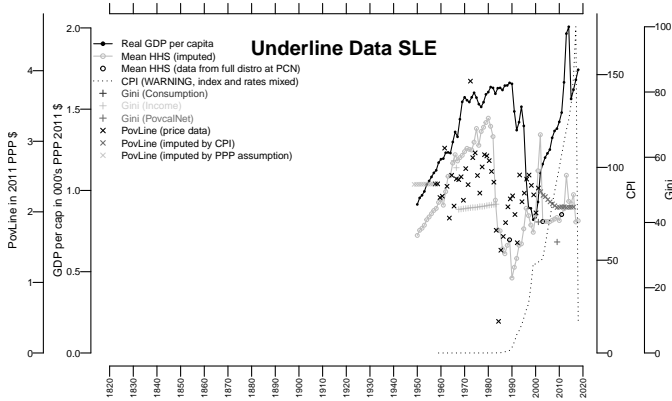
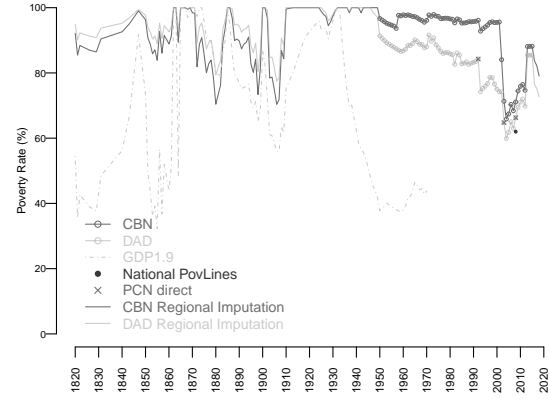
**Poverty Rates in Togo – TGO – Sub-Saharan Africa**



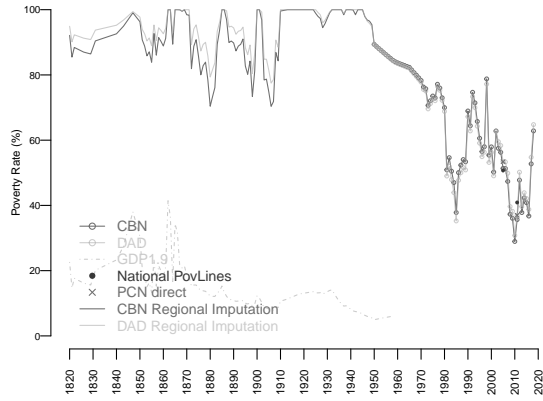
### Poverty Rates in Sierra Leone – SLE – Sub-Saharan Africa



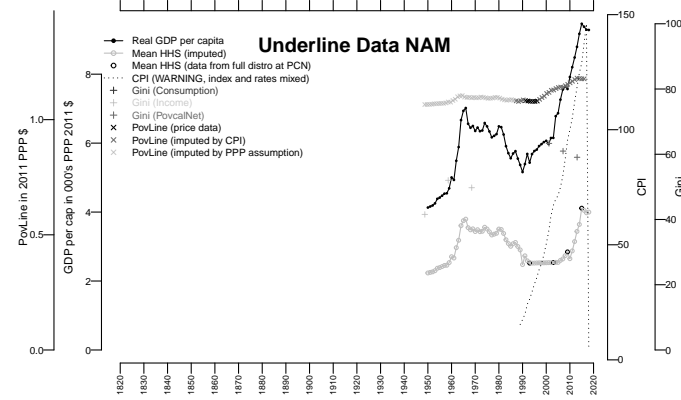
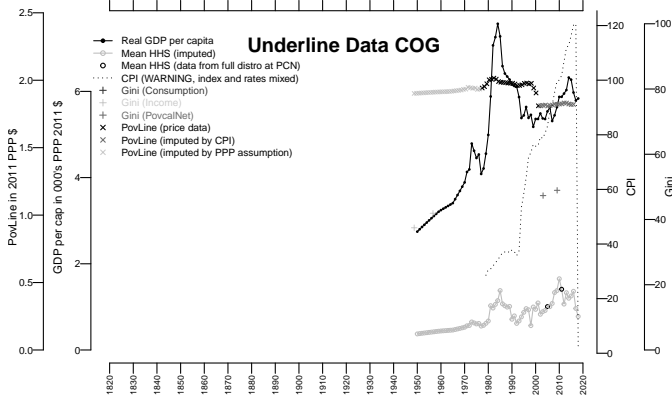
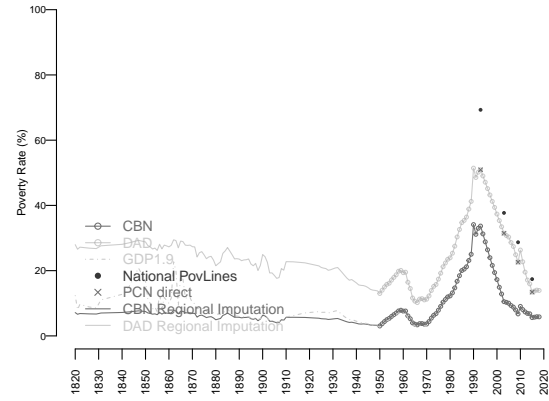
### Poverty Rates in Central African Republic – CAF – Sub-Saharan Africa



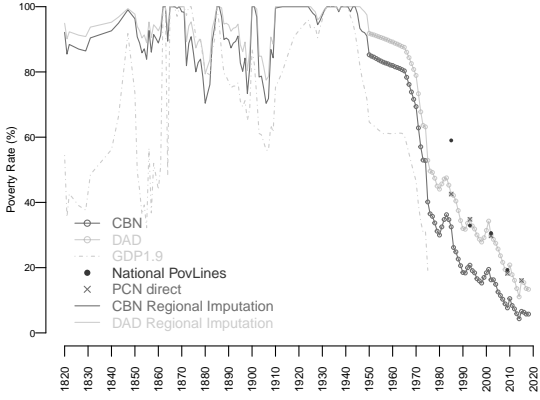
### Poverty Rates in Congo – COG – Sub-Saharan Africa



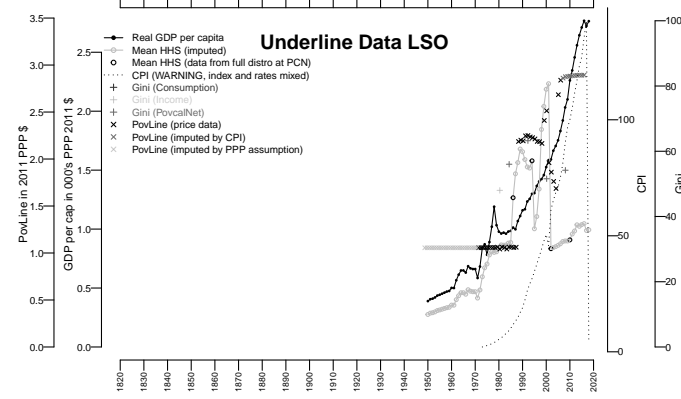
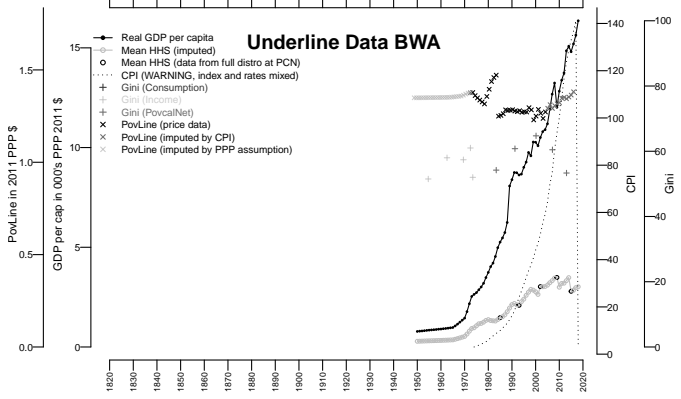
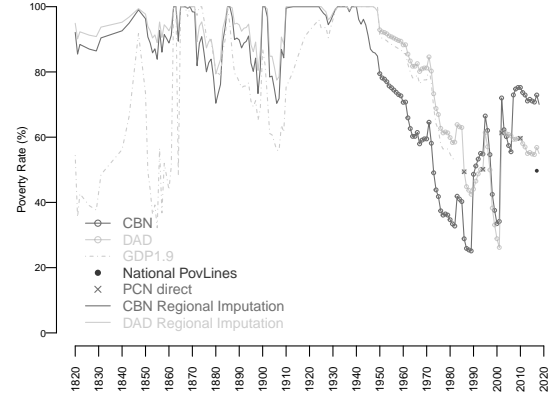
### Poverty Rates in Namibia – NAM – Sub-Saharan Africa



### Poverty Rates in Botswana – BWA – Sub-Saharan Africa

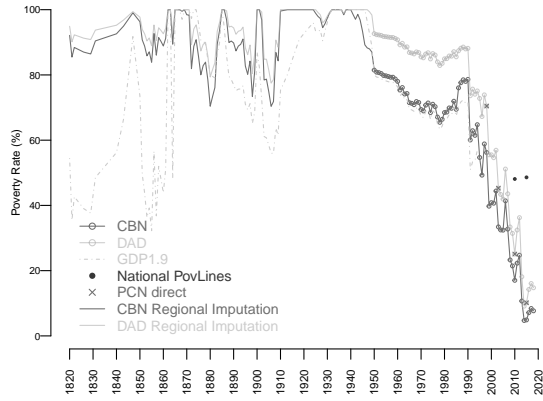


### Poverty Rates in Lesotho – LSO – Sub-Saharan Africa

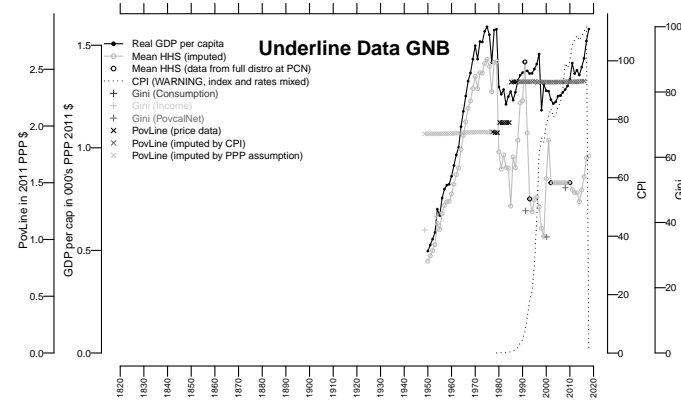
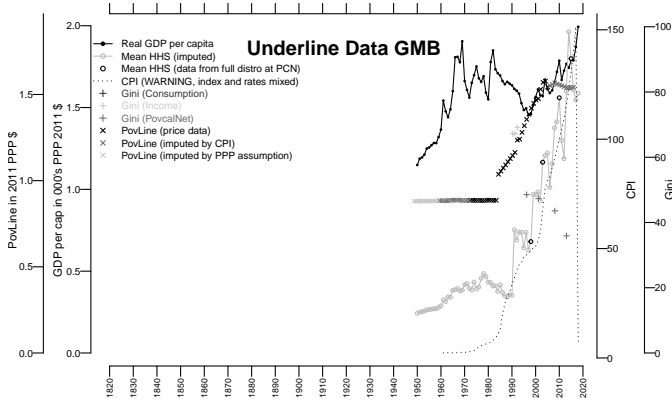
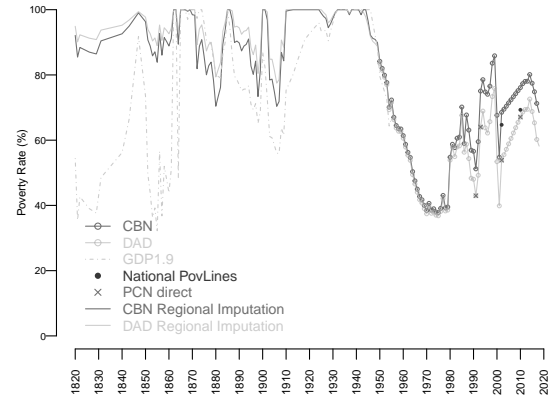




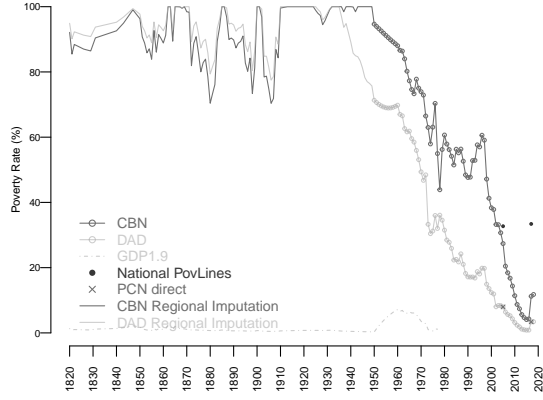
**Poverty Rates in Gambia – GMB – Sub-Saharan Africa**



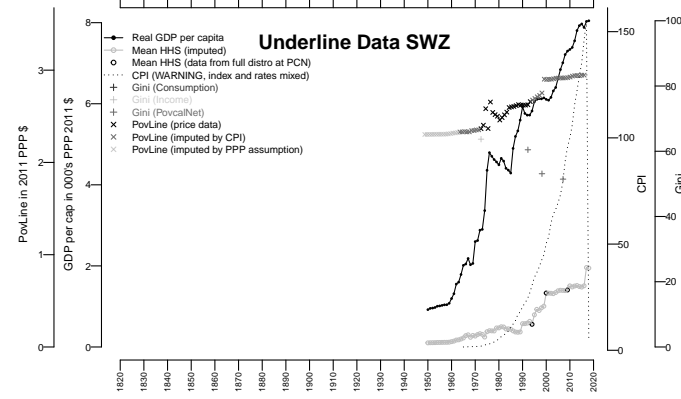
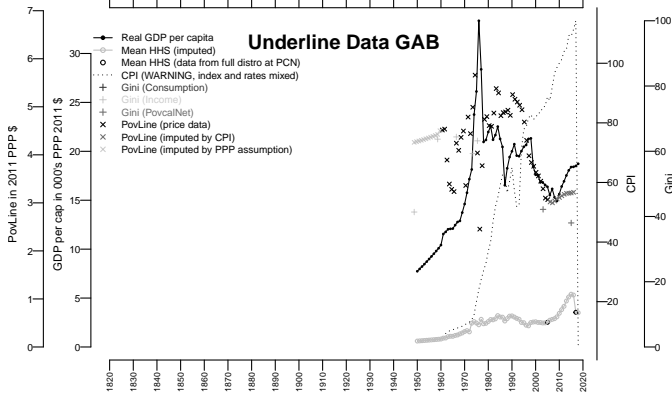
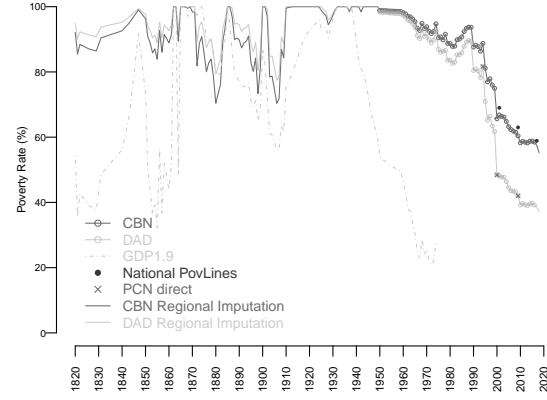
**Poverty Rates in Guinea-Bissau – GNB – Sub-Saharan Africa**



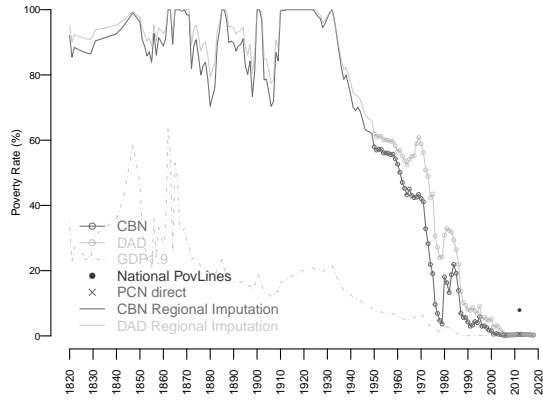
**Poverty Rates in Gabon – GAB – Sub-Saharan Africa**



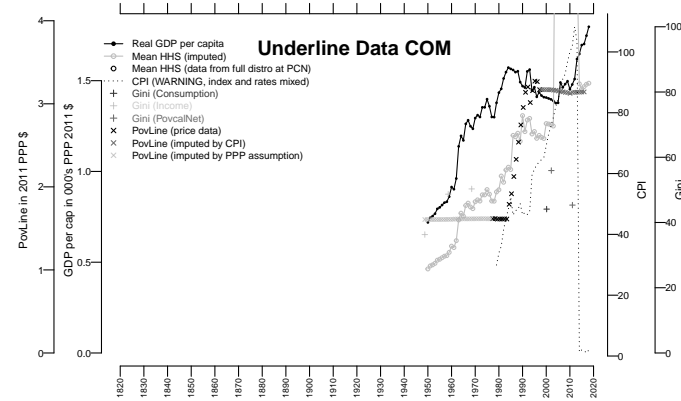
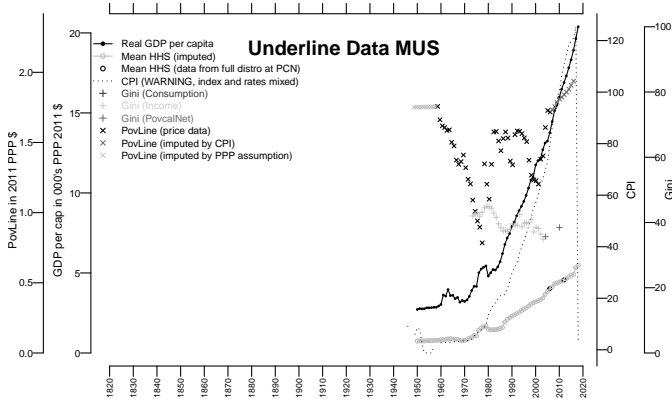
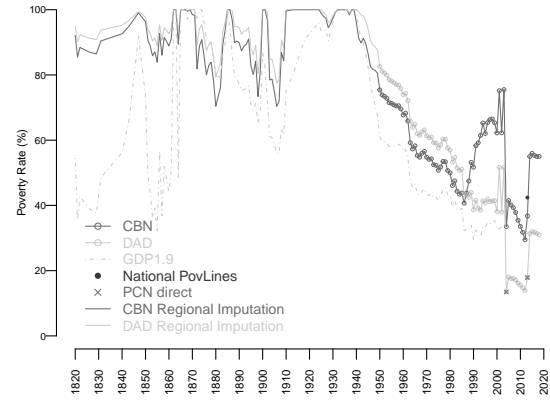
**Poverty Rates in Swaziland – SWZ – Sub-Saharan Africa**



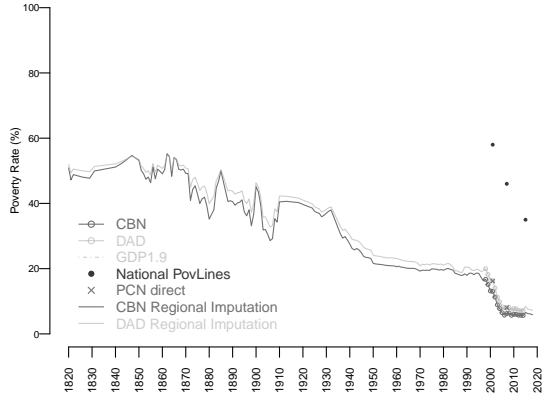
**Poverty Rates in Mauritius – MUS – Sub-Saharan Africa**



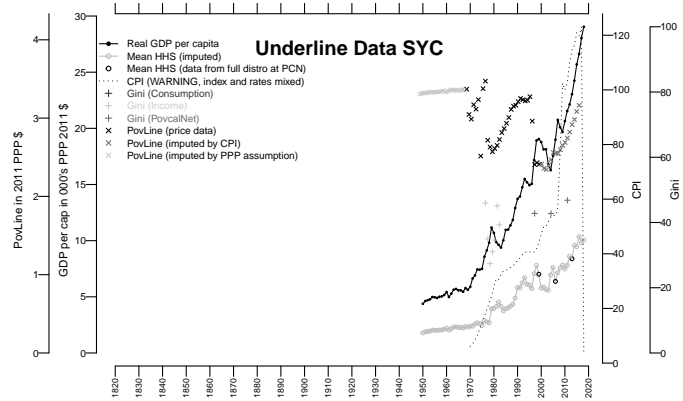
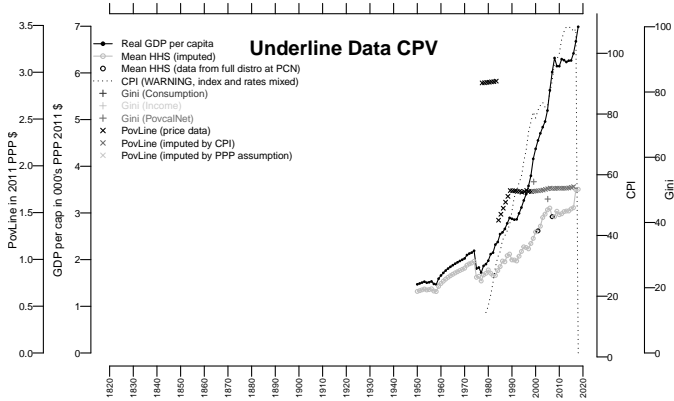
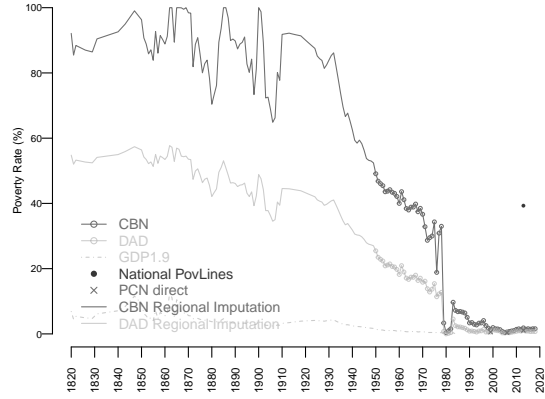
**Poverty Rates in Comoros – COM – Sub-Saharan Africa**



### Poverty Rates in Cabo Verde – CPV – Sub-Saharan Africa

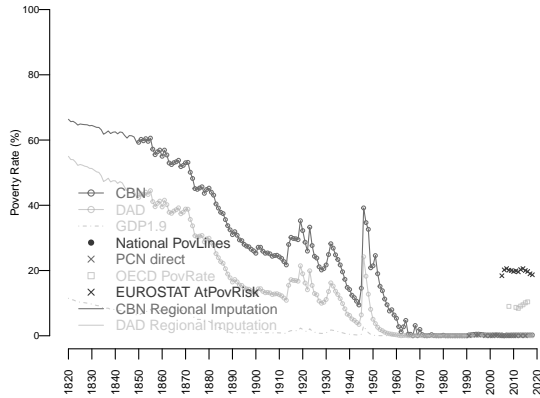


### Poverty Rates in Seychelles – SYC – Sub-Saharan Africa

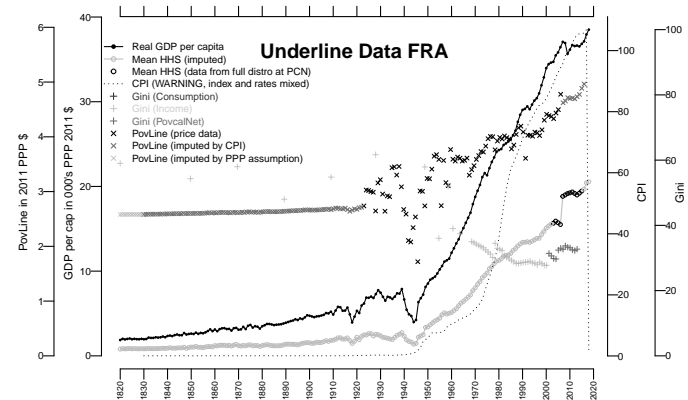
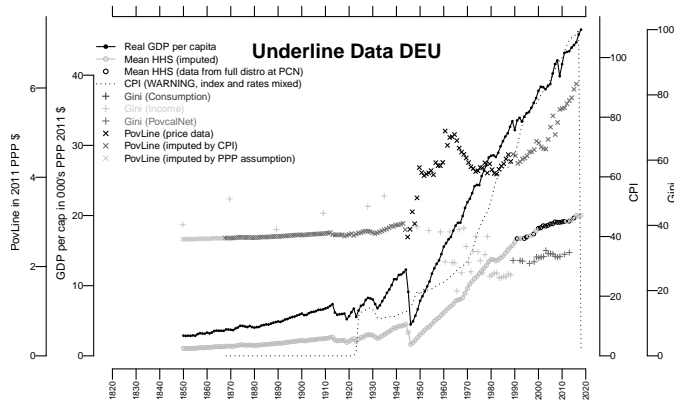
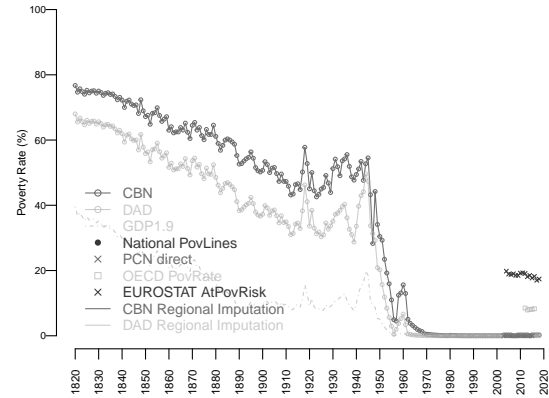


## 7.2.16 W. Europe

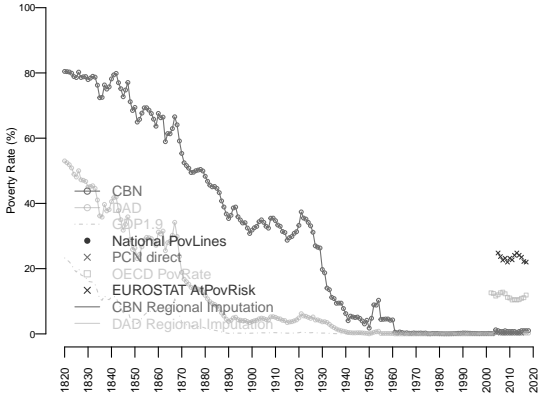
### Poverty Rates in Germany – DEU – W. Europe



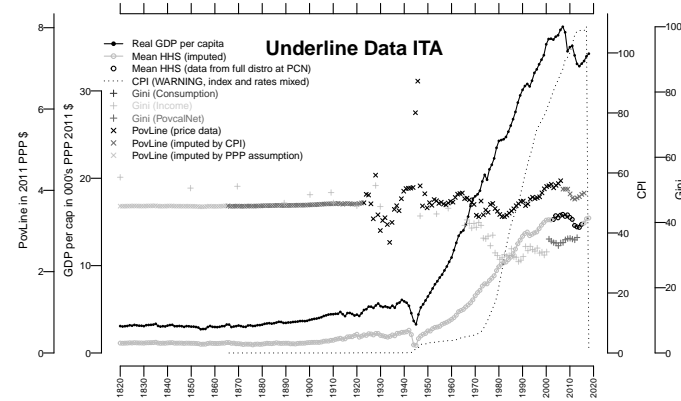
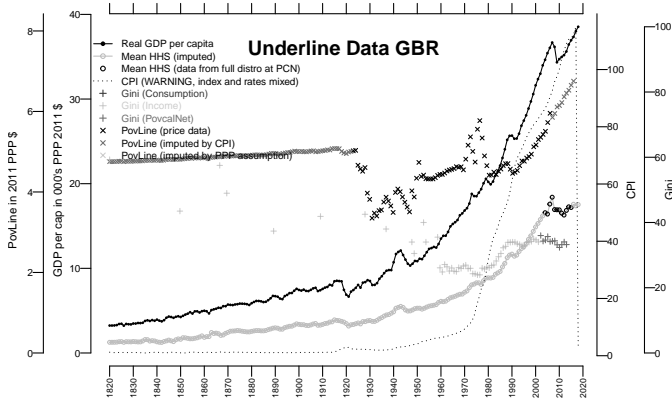
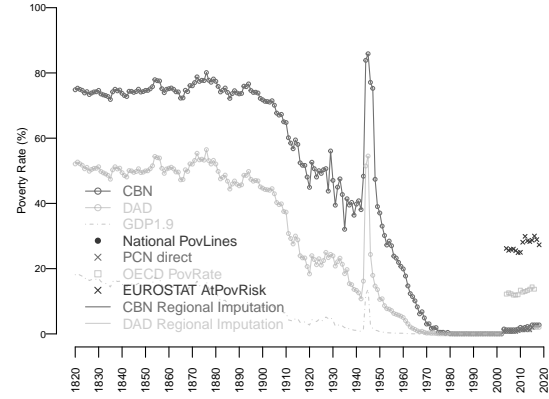
### Poverty Rates in France – FRA – W. Europe



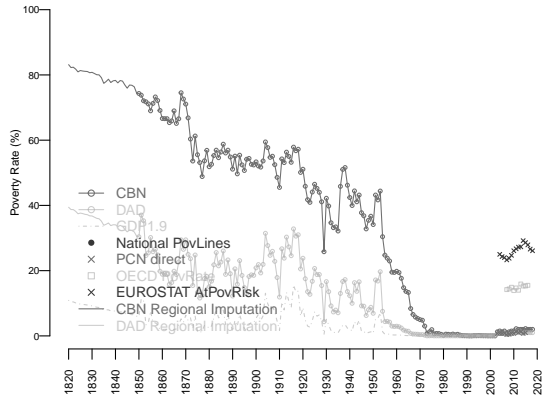
**Poverty Rates in United Kingdom – GBR – W. Europe**



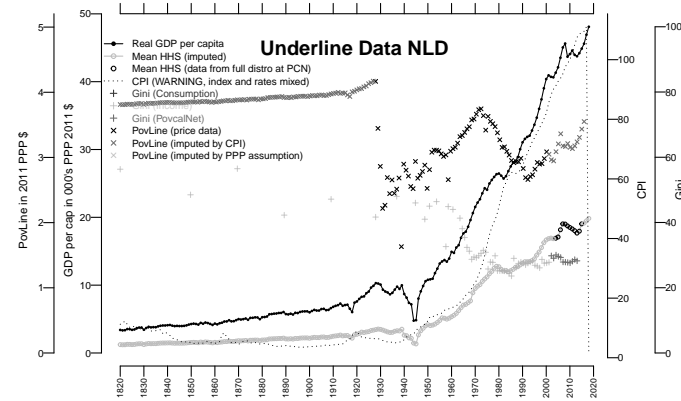
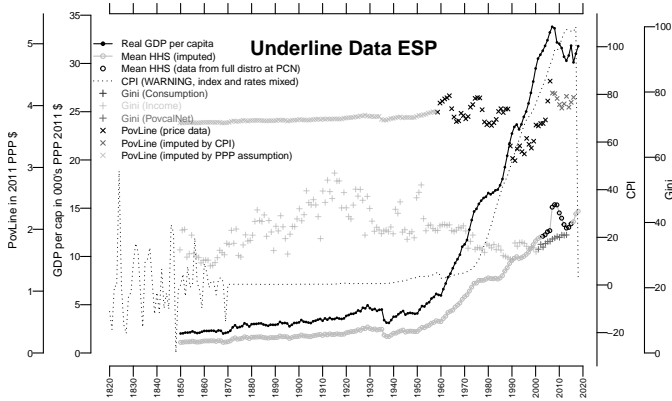
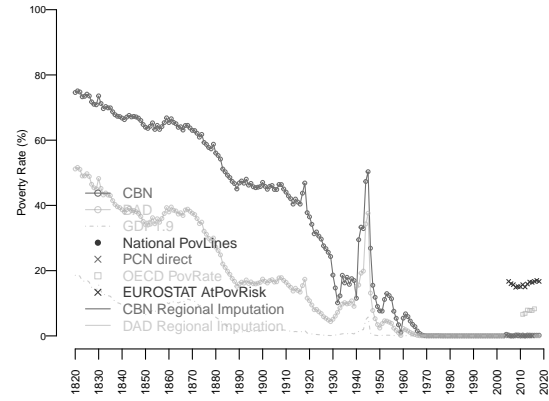
**Poverty Rates in Italy – ITA – W. Europe**



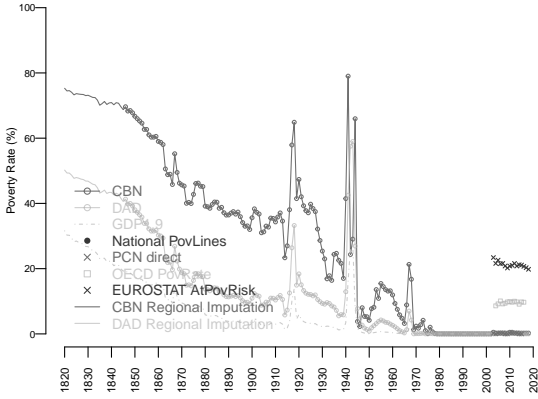
Poverty Rates in Spain – ESP – W. Europe



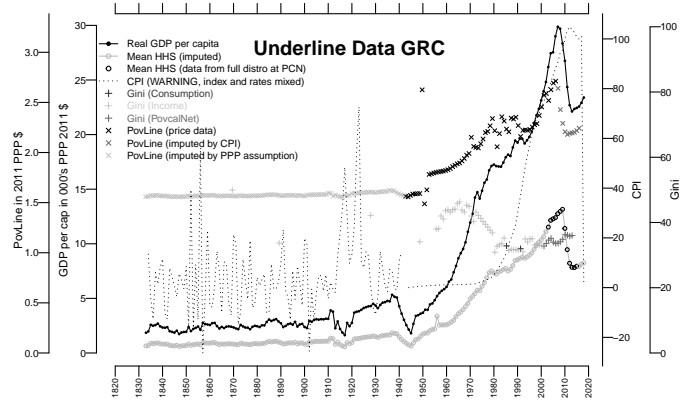
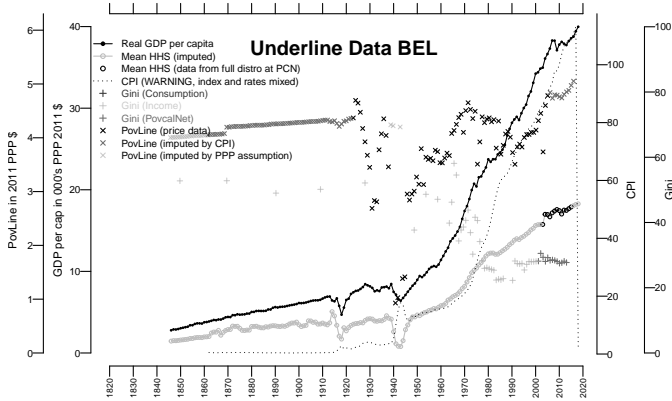
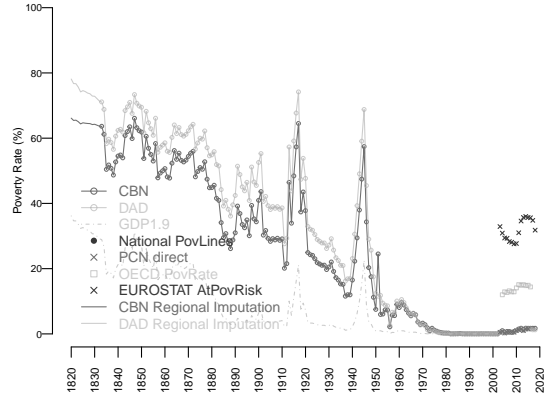
Poverty Rates in Netherlands – NLD – W. Europe



### Poverty Rates in Belgium – BEL – W. Europe

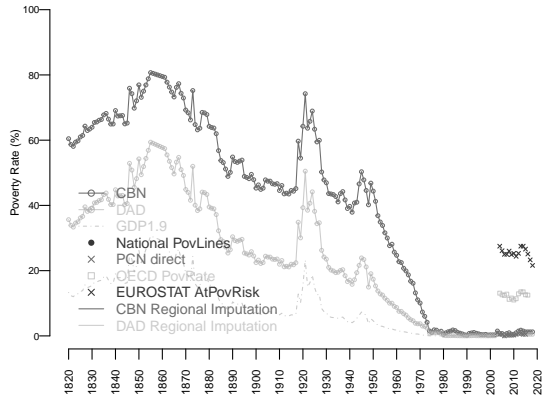


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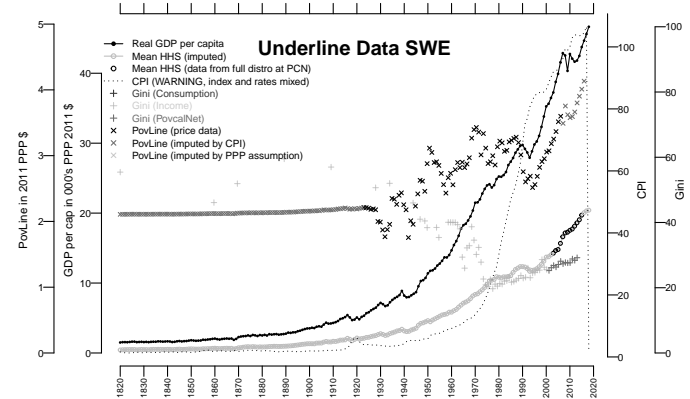
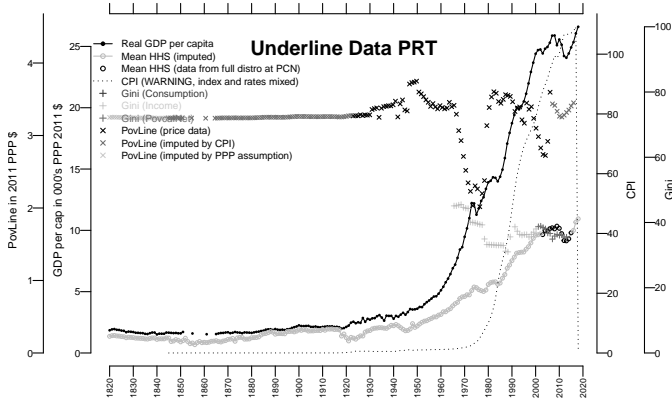
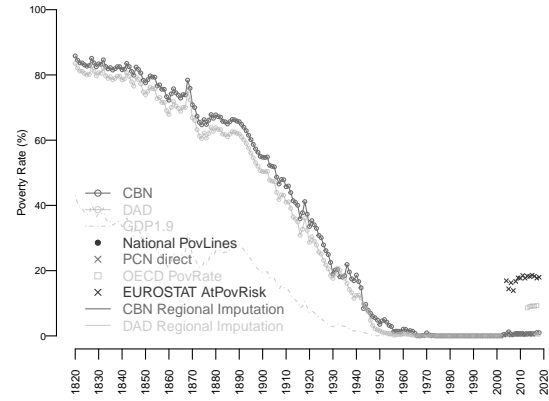




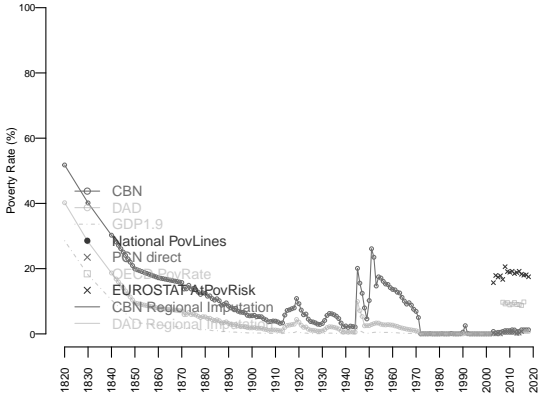
**Poverty Rates in Portugal – PRT – W. Europe**



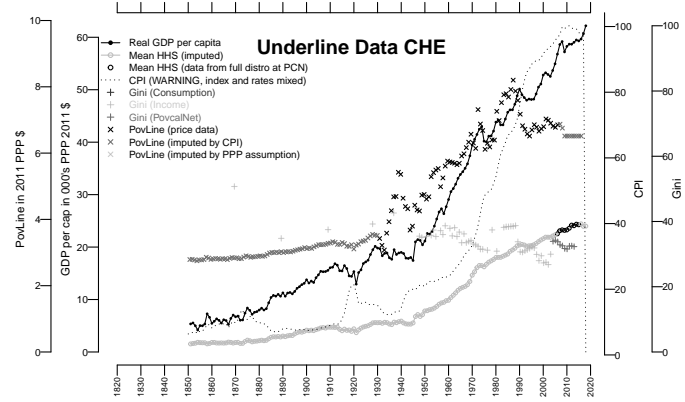
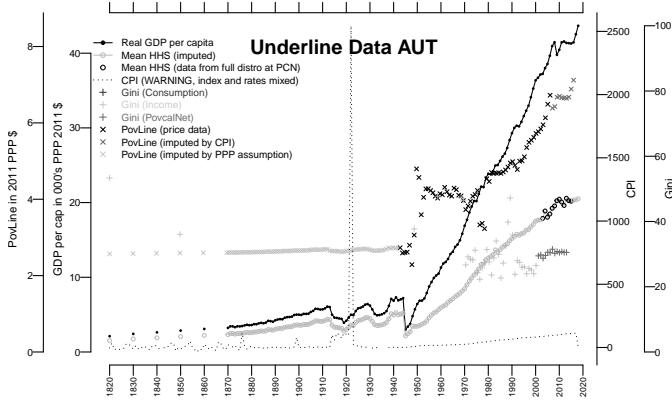
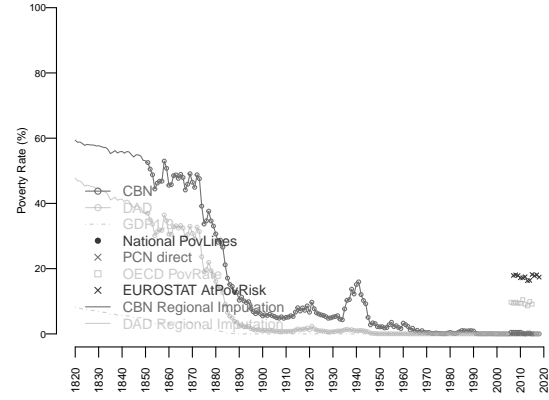
**Poverty Rates in Sweden – SWE – W. Europe**



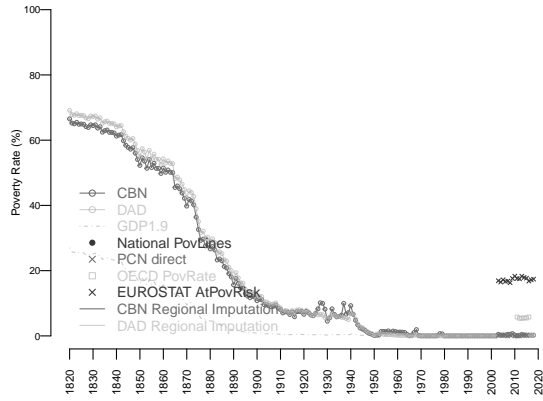
### Poverty Rates in Austria – AUT – W. Europe



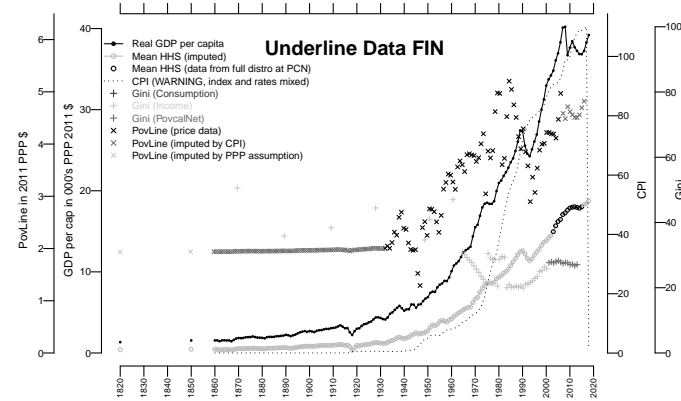
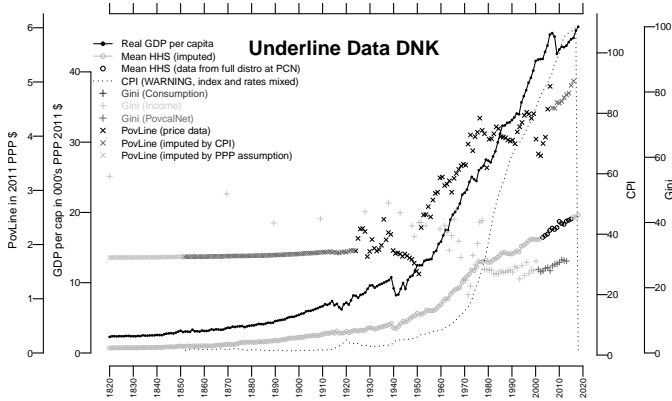
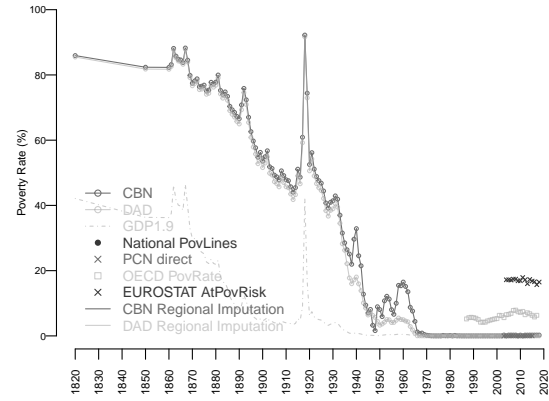
### Poverty Rates in Switzerland – CHE – W. Europe



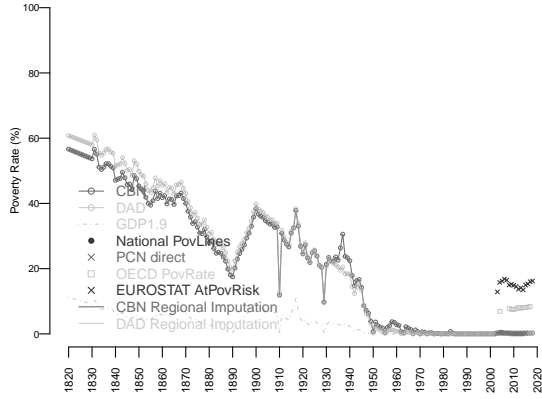
**Poverty Rates in Denmark – DNK – W. Europe**



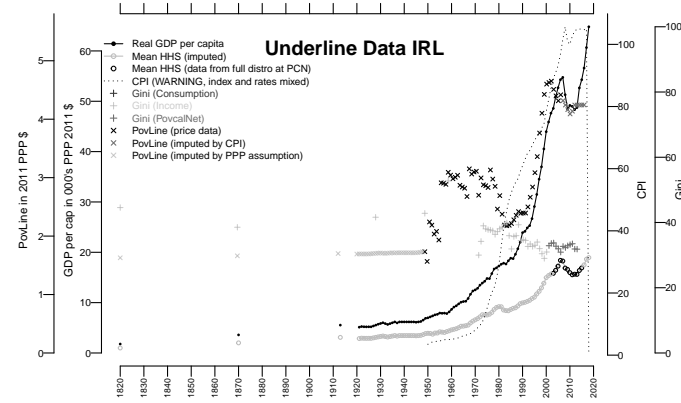
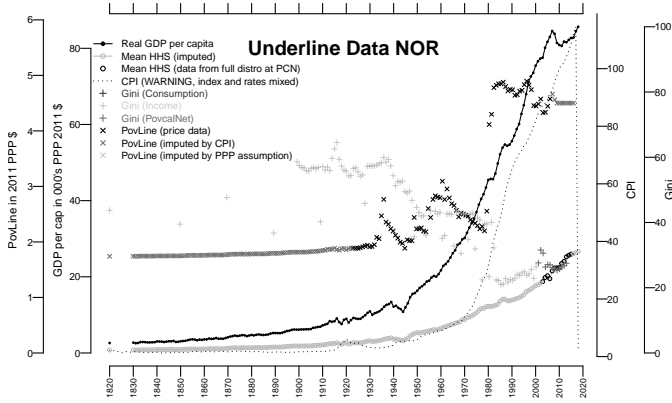
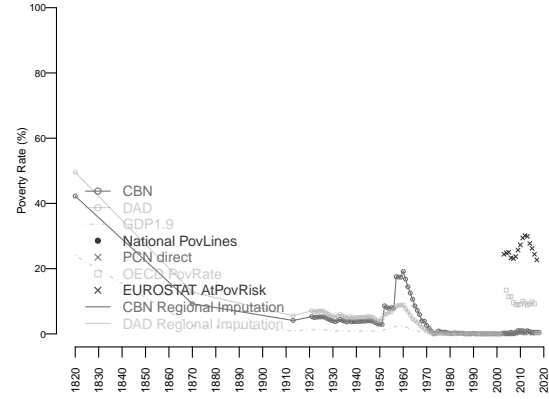
**Poverty Rates in Finland – FIN – W. Europe**



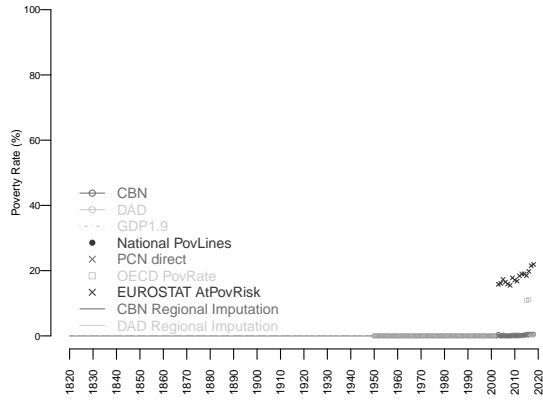
**Poverty Rates in Norway – NOR – W. Europe**



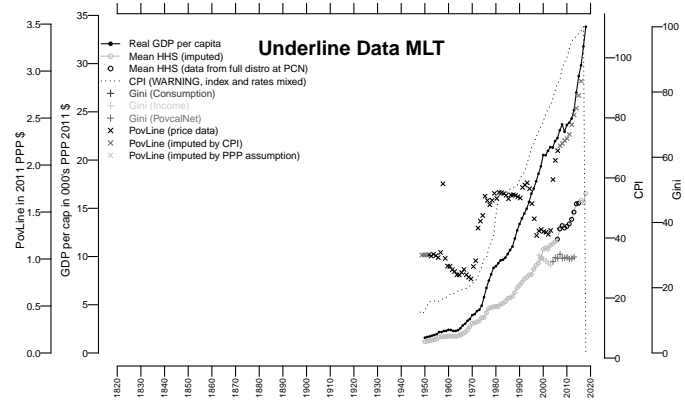
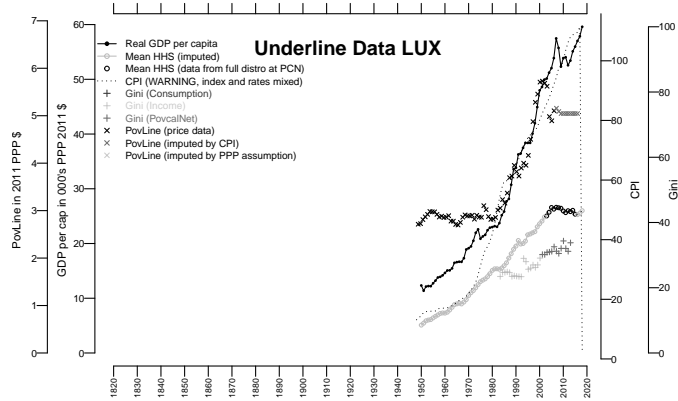
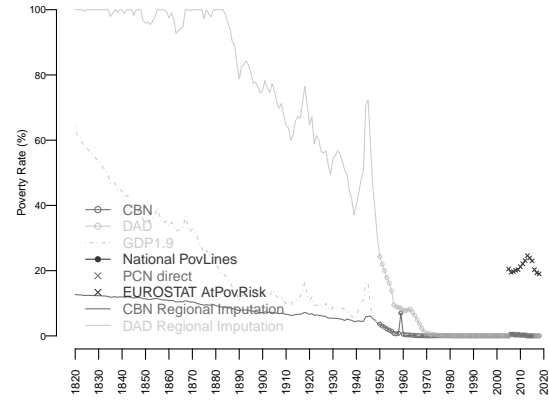
**Poverty Rates in Ireland – IRL – W. Europe**



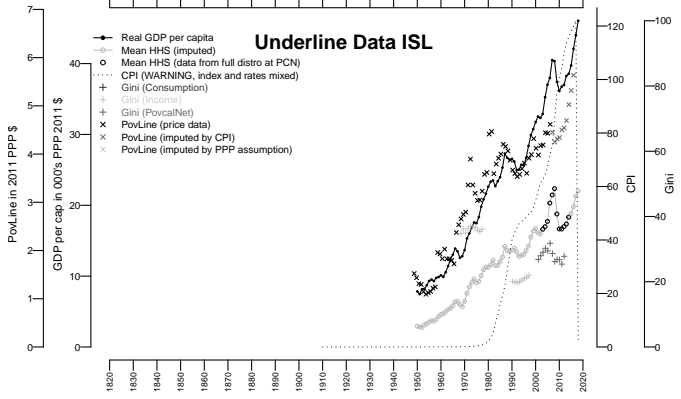
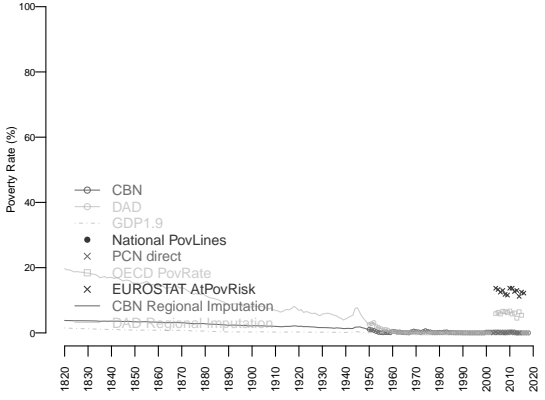
### Poverty Rates in Luxembourg – LUX – W. Europe



### Poverty Rates in Malta – MLT – W. Europe

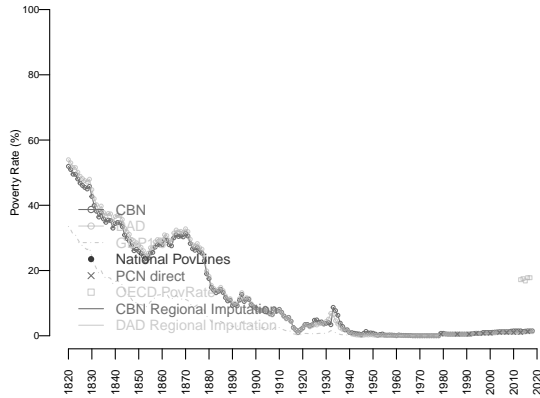


### Poverty Rates in Iceland – ISL – W. Europe

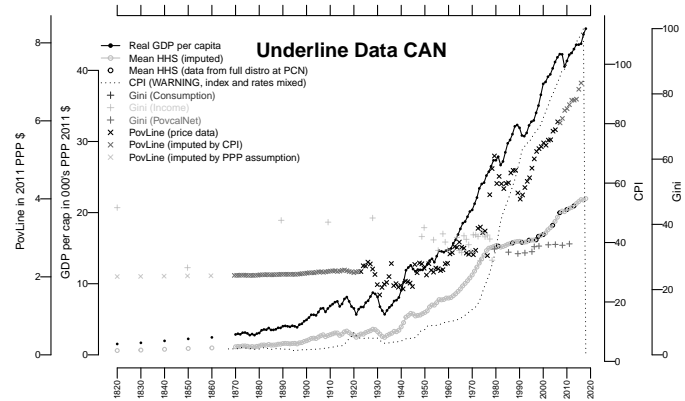
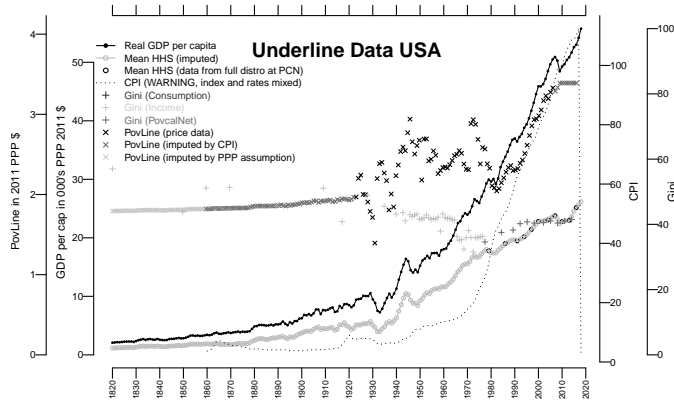
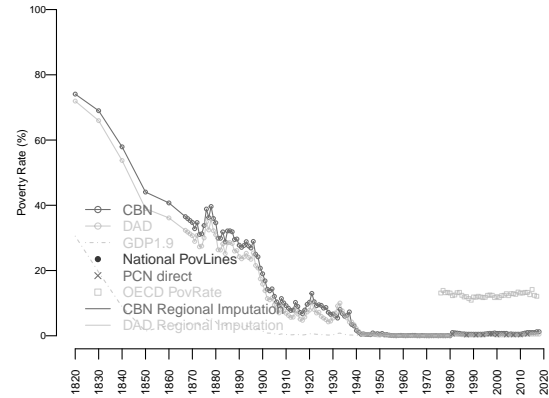


## 7.2.17 W. Offshoots

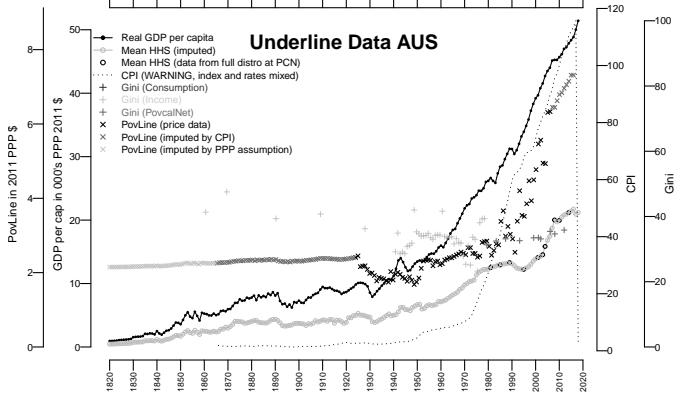
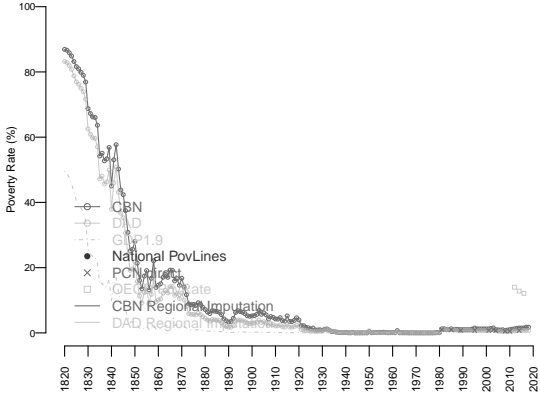
### Poverty Rates in United States – USA – W. Offshoots



### Poverty Rates in Canada – CAN – W. Offshoots



### Poverty Rates in Australia – AUS – W. Offshoots





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## **Author's Short Bio**

I am a PhD candidate at the Economic and Social History group in Utrecht University. Prior to this engagement, and after receiving a bachelor in Physics, and a master degree in Electronic Automation (both from University of Athens), I held managerial and research positions at the National Center for Scientific Research “Demokritos” in Athens (GR), and ventured in the realms of the corporate world as an entrepreneur in producing TV commercials and motion pictures, and reclaiming cash for online buyers. After those ventures I sought to get myself one more master degree, this time in Multidisciplinary Economics, a decision that fortunately brought me at Utrecht University from far.

My research evolves around the topics of wellbeing and poverty, as well as that of income distribution and inequality in a long run and global scale. In my research I consider the role of nominal prices as essential in the identification of various types of poverty. Most likely because of my background in natural sciences, I strongly prefer to deliver my estimates with an appropriate error term; as they ought to be delivered. This is the reason I lately delve into Monte Carlo micro-simulations in order to investigate the confidence interval around the poverty estimates and the level of statistical significance in the changes of global poverty rates. Since June 2020, I am also a post doc researcher at Bocconi University in Milan.

An additional line of research interests, not unrelated to what was mentioned above, is the measurement and evolution of wellbeing using composite indexes.<sup>6</sup>

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<sup>6</sup>See Stegeman et al. (2017) and Rijpma et al. (2017).



**Sanjay G Reddy**

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Following



I have been catching up on the literature on global poverty estimates that I have been remiss in reading recently, including, inter alia, the valuable work of [@mmoatsos](#), for which many thanks.

11:18 AM - 4 Mar 2019

**Sanjay G. Reddy, Associate Professor of Economics, The New School for Social Research, NY**

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