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Economic Complexity and Inequality

Does Productive Structure Affect Regional Wage Differentials in Brazil?

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Economic Complexity and Inequality: Does Productive Structure Affect Regional Wage Differentials in Brazil?

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Abstract

Brazil is an upper middle income economy, with a GDP per capita of close to 12,000 (constant) dollars in 2014. Nonetheless, Brazil has a significant amount of people living under poverty. 7.6% of the population was poor in 2014 (Poverty headcount ratio at $3.10 a day, 2011 PPP), making Brazil one of the most unequal countries in the world. Concomitantly, Brazil's different regions and states are highly heterogeneous with respect to income levels, inequality, and prevalence of poverty. Moreover, in the last past decades, the dispersion of inequality between states has increased. This paper shows that Brazilian states are also heterogenous in terms of economic complexity; and analyzes how economic complexity affects income inequality. To test the relationship between economic complexity and income inequality we employ panel data analysis for the 27 Brazilian states over the period 2002-2014. Our main proposition is that economic complexity affects regional wage differentials in a nonlinear way. Our findings confirm this proposition and point to an inverted U-shaped relationship, whereby higher economic complexity is initially associated with higher, and subsequently lower, inequality levels.

Keywords: Income inequality, economic complexity, Brazil, productive structure, Kuznets curve, wage differentials, Gini, Theil, economic development, Brazilian states, panel data, ECI

JEL classification: F63, I30, O54

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1 Introduction

The negative effects of income inequality on an economy are intuitive to many people. They include social unrest and underuse of a country's resources (United Nations, 2013). Nonetheless, income inequality is high in many countries, such as the United States and Brazil, which had a Gini index of respectively, 41.1 and 52.9 in 2013 (World Bank, 2017a).[1] From an academic perspective no success has yet been achieved in explaining the cross-country differences in income inequality. According to Sachs (2015), while income inequality was traditionally strongly related to history, geography and institutions, nowadays, income inequality is also influenced by the productive structure of an economy (e.g. the size of the industrial sector).

In this paper, we take Sach's argument one step further while trying to explain current income inequality within Brazil. Our main proposition is that *economic complexity* of the different Brazilian states affects their level of income inequality in a nonlinear way. Economic complexity, as described by Hausmann et al. (2014b), reflects the amount of knowledge embedded in the productive structure of an economy, which depends both on the diversity of all individual knowledge and on the ability of individuals to combine and translate it into knowledge-intensive products and large networks of interaction.

Economic development pioneers saw a country's productive structure as an important determinant of its ability to generate and distribute income (e.g. Rosenstein-Rodan (1943); Singer (1950); Hirschman (1988)). Nevertheless, since the work of these authors, only simple quantitative approaches – such as measuring the fraction of an economy employed in different sectors, or using aggregate measures of diversity and concentration – had been used while trying to quantify this relationship. These measures of a country's productive structure, however, fail to take the sophistication of products into account and do not capture differences in industrial structures in a comprehensive way. The recent emergence of measures of economic complexity has expanded our ability to quantify a country's productive structure (Hartmann et al., 2017a).

By focusing on the knowledge embedded in production, as opposed to simply looking at quantities produced or the factors of production and technology employed, economic complexity gives a deeper understanding of what a country is producing and what is involved in that activity. As economic complexity changes, rewards to different skills and levels of knowledge change, resulting in a direct impact on wage differentials. More specifically, as economic complexity rises, the demand for knowledge increases, and thus also the demand for skilled labor. The result is an increase in the dispersion between skilled and unskilled workers' wages. On the

[1]Compare with the Gini in the Netherlands, for example, which was 28.0 in 2012 (World Bank, 2017a).

other hand, after a certain level of economic complexity is achieved, returns to higher education levels may decrease, thus lowering inequality between skilled and unskilled workers' wages.

The aforementioned channel through which economic complexity relates to income inequality resembles the motivation for the Kuznets (1955) curve, which predicts an inverted U-shaped relationship between GDP per capita and income inequality. However, even though changes in economic complexity are associated with economic development – in fact, Hausmann et al. (2014b) argue that economic complexity is a driver of economic growth – economic development, as measured by GDP per capita, relates to many things other than the productive structure of an economy, which are strongly related to income inequality, such as institutions. Therefore, by looking at economic complexity separately from economic development, we can better assess the differences in income inequality across countries or within a particular country.

Brazil provides an ideal setting to explore this question. Even though it is not among the poorest countries in the world, Brazil has a high poverty level (7.6% of the population was poor in 2014[2]), meaning that it is one of the most unequal countries in the world. Concomitantly, Brazil's different regions and states are highly heterogeneous and the dispersion of inequality between states has increased over the past decades (Castilho et al., 2012). Brazil is also an ideal country for this research because it offers data at different aggregation levels - namely at the region, state, mesoregion, microregion, and municipality levels. The aim of our research is therefore to understand the relationship between economic complexity and income inequality in Brazil.

This paper is organized as follows: Section 2 provides a literature review, starting with a brief presentation on the links between economic complexity and inequality, and focusing thereafter on inequality in Brazil. Section 3 looks at economic complexity, income and inequality in Brazilian states, providing a background data analysis. Section 4 presents the data and methodology used in our research. Section 5 outlines the estimation results, followed by several robustness checks presented in Section 6. Finally, Section 7 presents a discussion of our results and their implications, followed by the conclusion.

[2]Poverty headcount ratio at $3.10 a day (2011 PPP), World Development Indicators, World Bank.

2 Literature Review

2.1 Economic Complexity and Inequality

Theoretically, the relationship between economic complexity and income inequality is not new. Pryor (1996) relates structural complexity to the organization of a system. According to this author, increased direct information requirements, increasing interactions within the system, and increasing heterogeneity of the economic system are all associated with increasing structural complexity. Hodgson (2003) defines increasing economic complexity as a growing diversity of interactions between human beings and between people and their technology. More specifically, the author analyzes the impact of growing complexity on the level, diversity and distribution of skills in the economy. One of his propositions is a world where robots take over most of the production, thus leading to menial jobs and unemployment - economic complexity might be increasing, without an increase in knowledge and skill. This suggests that increased economic complexity leads to more inequality and higher wage differentials. Hidalgo and Hausmann (2009) developed an index for measuring economic complexity, which allows an empirical analysis linking economic complexity to inequality levels. Hartmann et al. (2017a) use this index to examine whether more complex economies have lower levels of income inequality. Using data for over 150 countries for the period between 1963 and 2008, the authors test for a linear relationship and find robust evidence that economic complexity is a negative predictor of income inequality. Furthermore, the authors highlight that, when controlling for economic complexity, the rising part of the Kuznets curve is more pronounced than without it.

In addition to looking at the general relationship between economic complexity and income inequality, Hartmann et al. (2017a) also explore the inequality related to 775 particular product categories. The authors show that the products associated with the highest levels of income inequality (high Product Gini Index, PGI) consist mainly of commodities – such as cocoa beans and animal hair – which have a low level of economic complexity; whereas low PGI products include more sophisticated forms of machinery and manufacturing products – such as textile machinery and road rollers – which involve a high level of economic complexity. The intuition behind these findings is straightforward. Complex products require a larger network of skilled workers, related industries, and inclusive institutions for economic competitiveness. These characteristics are conducive to more equal societies. In contrast, the competitiveness of simple industrial products and resource exploiting activities is mainly based on resource richness, low labor costs, routinized activities and economies of scale. These characteristics lead to more unequal economies.

Hartmann et al. (2017b) look at the structural constrains of income inequality in

Latin America. The authors compare the productive sophistication and structural constraints on income inequality of Latin American and Caribbean countries with that of China and other high-performing Asian economies. Their results show that Latin American and Caribbean countries continue to export products associated with high levels of inequality and low levels of economic complexity, and their productive structure strongly constraints their ability to generate and distribute income (Hartmann et al., 2017b).

Similarly, Hausmann et al. (2014a) also point towards linkages between economic complexity and income inequality. The authors look at opportunity value, or rewards to knowledge accumulation, and how it relates to economic complexity. Their data show that countries with a low ECI have low rewards to knowledge; this is because countries with low ECI, cannot effectively put knowledge into productive uses. However, countries with high levels of productive knowledge also have low rewards to knowledge; the authors justify this with the fact that, in these countries, productive knowledge already occupies a large fraction of the product space and thus there are diminishing returns to further knowledge accumulation. Finally, countries with an intermediate level of complexity vary widely in their opportunity value. If we associate opportunity value with wages, this indicates that the relationship between the ECI and wage differentials is not a linear one. Instead, based on Hausmann et al. (2014a) we expect it to be an inverted U-shape.

2.2 Inequality in Brazil

2.2.1 Evolution of Inequality in Brazil

Figure 1 shows the evolution of the Gini coefficient for Brazil from 1976 to 2014.[3] From 1976 until 1980 Brazil experienced a decrease in inequality, which was offset by a large increase between 1981 and 1989. However, what stands out in the figure is the steadily decrease of inequality from 1993 onwards, with a particularly accentuated decrease after 2002. Brazil's Gini coefficient decreased from 0,604 in 1993 to 0,518 in 2014. Accordingly, most of the studies on Brazil's income inequality make a distinction between two main periods, 1981-early 1990s and 1993 onwards (Ferreira et al., 2007). A few authors focus solely on one of these periods (e.g. Azzoni and Servo (2002); Cardoso et al. (1995); Borraz et al. (2013)), while others focus on both and explicitly try to differentiate the determinants of inequality in each period (e.g. Ferreira et al. (2006)). Within this literature there is no consensus with respect to the driving forces behind the changes in inequality in Brazil. While all studies seem to agree on the fact that inequality in Brazil was not driven by the same factors throughout each of the two time periods, not all find the same major driving force

[3] Based on data from the Institute for Applied Economic Research (IPEA)

for each of these periods.

[Figure 1] ABOUT HERE

Azzoni (2001) analyzes the evolution of inequality between Brazilian regions for the period from 1939 to 1995 and looks at the dispersion of per capita income among regions and at the correlation between a region's initial level of income per capita and its growth, testing for Beta convergence. The author shows that inequality was decreasing within wealthier regions of the country and increasing within the poorer regions, which is in accordance with the Kuznets hypothesis. Azzoni (2001) provides, however, no explanation behind these different economic processes at play in Brazil.

Apart from Azzoni (2001), to the best of our knowledge, no other paper has investigated the Kuznets hypothesis for Brazil, or the relationship between economic growth and inequality. Rather, research on inequality in Brazil has focused on two main sets of explanatory variables. The first set involves education and the wider macroeconomy (in particular unemployment and inflation). The second set, focuses on international trade.

Ferreira et al. (2006) study the rise and fall of Brazilian inequality between 1981 and 2004, through static and dynamic decompositions of inequality. Their results show that the drivers of inequality differed between the two aforementioned periods (1981-1992 and 1993-2004). The increase in inequality observed throughout the 1980s was associated with two main factors. The first was an expansion in the levels of formal education in the labor force, which led to greater inequality between educational sub-groups of the population. The second factor was the accelerating rate of inflation, which is likely to have a regressive impact on the income distribution.

The subsequent decrease in inequality from 1993 onwards, however, seems to be driven by other forces. The authors introduce four candidate explanations, namely: sharp declines in the returns to education, which appear to be driven by a reduction in the average returns to schooling in Brazil; pronounced rural-urban convergence; increases in social assistance transfers targeted to the poor; and a possible decline in racial inequality.

Azzoni and Servo (2002) assess whether worker characteristics (in particular education, age, gender, race and position in the family) and job characteristics (such as occupational position, sector and experience) explain wage inequality. The focus is on the 10 largest metropolitan regions in Brazil, during the 1990s. Their results indicate that, while the different levels in living costs across regions have a role in explaining wage inequality in Brazil, there are significant regional differentials that remain unexplained after controlling for this. On this front, the most important variable in explaining wage differentials is education, with the highest marginal contribution of all variables, followed by region, experience, and race, with the three having a similar level of importance.

Other researchers have claimed that education cannot explain fluctuations in inequality in Brazil over all time periods. For instance, Cardoso et al. (1995) claim that, while education explained the change in inequality during the 1960s, it fails to do so for the 1980s. Rather, the authors find unemployment and inflation to be the main culprits for the rising trends in inequality. More specifically, their results show that variations in inflation and unemployment explain approximately one-third of all variation in the level of inequality in all metropolitan areas (with the exception of São Paulo). Overall, both unemployment and inflation increase inequality. Inflation does this by pushing the middle-income groups into poverty (inflation reduces the real income of all educational groups but affects more strongly the group in the middle).

More recently, Barros et al. (2010) focus on Brazil as a whole between 2001 and 2007 and estimate the contribution of public policy and the performance of markets to the evolution of income inequality. Their paper suggests that the recent decline in inequality was a result of three main factors. First, an increase in contributory and non-contributory government transfers. Second, a decline in wage differentials by educational level and reductions in the inequality in education caused by an accelerated expansion of labor force educational level. Third, an improvement in spatial and sectoral integration of labor markets, in particular among metropolitan and non-metropolitan areas.

In addition to education and the wider macroeconomy, the impact of international trade has also been identified as a determinant of inequality in Brazil. Figure 2 presents data on simple mean tariff on trade for Brazil, using World Bank data. Brazil went through a period of significant trade liberalization between 1989 and 1995, with tariff levels remaining relatively stable in the subsequent periods, particularly from the early 2000s onwards. Trade liberalization has received significant attention in Brazil because it impacted the country differently than it did in other Latin American countries. In countries such as Colombia and Mexico, trade liberalization was associated with, and blamed for, a pronounced increase in inequality, which countered the predictions of the HO model and the SS theorem (Castilho et al., 2012). In Brazil, however, trade liberalization impacted wage inequality in the opposite direction (e.g. Ferreira et al. (2007); Gonzaga et al. (2006)). Nevertheless, some ambiguity in the empirical evidence for Brazil remains.

[Figure 2] ABOUT HERE

Helpman et al. (2017) develop a theoretical model consistent with the observed cross-sectional patterns of wages, employment and export status across firms, and a methodology for estimating it, in order to quantify the contribution of trade to wage inequality through the mechanism of firm selection into international trade. The authors motivate their model on several stylized facts about wage inequality using Brazilian data from 1986 to 1998. The findings show that there are sizeable effects of trade on wage inequality, with the opening of the closed economy to trade raising the standard deviation of log worker wages by around 10 per cent. The estimated model implies a non-monotonic relationship between wage inequality and trade openness, where trade liberalization initially raises and later reduces wage inequality, with 1994 being the threshold year.

Ferreira et al. (2007) study the relative importance of trade-mandated effects on industry wage premia, industry and economy-wide skill premia, and employment flows in accounting for changes in the wage distribution in Brazil from 1988 to 1995, when trade liberalization occurred. The authors combine two different approaches used in the literature – namely, by Pavcnik et al. (2004) and Gonzaga et al. (2006) – and thus are able to estimate the combined effect of the two channels (industry-specific wage and skill premia, and the economy-wide skill premium) on the wage distribution in Brazil.

According to their findings, trade liberalization contributed towards the observed reduction in wage inequality. This outcome was a consequence of the pre-liberalization tariffs being the highest for skill-intensive goods, meaning that they fell by more than those for other goods, leading to a decline in relative prices. This decline led to a reduction in skilled worker wages, relative to those of unskilled workers, and to a movement of workers away from previously protected industries. This outcome was therefore consistent with the SS theorem (Ferreira et al., 2007).

Prior to the paper by Ferreira et al. (2007), other researchers found different answers to the question of how trade liberalization impacted income inequality. For instance, Pavcnik et al. (2004) find no evidence of any effect from trade liberalization on the Brazilian wage distribution. Gonzaga et al. (2006) argue that, through the more general channel of changes in the economy-wide skill premium (as opposed to industry-specific premia), trade liberalization reduced wage disparities in Brazil. Finally, Castilho et al. (2012) look at trade liberalization and its impact on inequality and poverty across Brazilian states from 1987 to 2005. The authors find that trade liberalization significantly impacted inequality levels in Brazilian states. However, the direction of the impact differed between rural and urban areas. More specifically, while trade liberalization led to an increase in both inequality and poverty in urban areas, it led to a decrease in inequality (and possibly in poverty too) in rural areas. As a possible explanation for this phenomenon, the authors point out that trade liberalization for Brazil was more intense in manufacturing sectors, which are typically set up in urban areas. This has important implications for our paper, particularly if more complex industries are located in urban areas and least complex ones are located in rural areas.

Since Castilho et al. (2012) focus on regional differentials and carry out a well-rounded research across all industries in Brazil, it provides a good guide for our paper. Therefore we follow their approach closely in terms of control variables and general methodology in looking at how economic complexity (rather than trade liberalization) contributes to regional wage differentials and how this impact differs between rural and urban areas. All in all, this review of the existing literature demonstrates that inequality in Brazil remains a somewhat unexplained phenomenon which can benefit from further research and understanding. Our control variables will be in line with these findings of the drivers of inequality and are expected to follow similar signs.

3 Economic Complexity, Income & Inequality in Brazil

According to the Observatory of Economic Complexity, Brazil was ranked the 34th most complex economy (out of 184), with an ECI of 0.73 in 2015.[4] The ECI level for a country as a whole is not directly comparable to that of regions within a country. This is because, as will be further described, it takes into account the comparative advantage of a region in relation to the international market in exporting a certain product. Nonetheless, it is easy to see that within the country there is ample heterogeneity across states. For instance, the state of São Paulo is the most complex one, with an ECI of 124.44 in 2014, whereas the state of Santa Catarina, is the least complex one, and had an ECI of -13.33 that year.

Similarly, while Brazil is amongst the most unequal countries in the world, the level of inequality also differs significantly across states. More specifically, the federal district had the highest inequality level in 2014, with a Gini coefficient of 0.582, whereas the state with the lowest inequality level was that of Santa Catarina, with a Gini of 0.421 in the same year.

This section outlines trends in economic complexity, income per capita and inequality for Brazil at the state level. This is followed by a graphical representation of the relationships between these variables. The measure of inequality used throughout this section is the Gini coefficient. This data, along with the data for GDP per

[4] http://atlas.media.mit.edu/en/profile/country/bra/

capita is from IPEA. The ECI comes from SECEX (downloaded through DataViva).

3.1 Trends in Economic Complexity, Income and Inequality

Figure 3a depicts the ECI for all Brazilian states from 2002 to 2014. This figure shows that São Paulo has the highest ECI level and is well above the other states. Economic complexity remained relatively stable in São Paulo over this time period, with some decline after 2006. Figure 3b omits data for São Paulo. This figure shows a slight divergence between states over the period, with the ECI increasing in some states and decreasing in others. Most of the variation in the ECI occurs in states which have either relatively high or relatively low levels of economic complexity. In contrast, for states with levels of the ECI close to zero, economic complexity remained more stable throughout this time period.

Figure 4 shows the trends in income per capita for the Brazilian states from 2002 to 2011. The federal district has a significantly higher GDP per capita than all other states, and experienced a further increase over this time period. Figure 4b omits the data for the federal district. Here, it becomes clear that income per capita increased in all states throughout this period, and that there was no convergence between the different states.

Figure 5 illustrates the trends in the Gini coefficient for the Brazilian states from 2002 to 2014. Overall, the data shows a slight decrease in inequality over time across all states. The heterogeneity observed between the states remains present throughout this period, with no convergence observed between them.

[Figure 3] ABOUT HERE

[Figure 4] ABOUT HERE

[Figure 5] ABOUT HERE

3.2 Relationships between Economic Complexity, Income and Inequality

Figure 6 shows the relationship between inequality and economic complexity. São Paulo is a clear outlier (Figure 6a), with a significantly higher level of ECI than the other states, despite an average level of inequality. Figure 6a reveals no clear relationship between economic complexity and inequality. When the data for the state of São Paulo is omitted from the graph in Figure 6b, a positive relationship between economic complexity and inequality comes out of hiding, suggesting that higher economic complexity is associated with higher inequality.

Figure 7 shows the relationship between inequality and income per capita. In Figure 7a, all states are included, with the federal district as an outlier which has a significantly higher level of both income per capita and inequality. Despite the outlier, a negative relationship between the variables is apparent. Figure 7b presents the same plot without the data for the federal district. The relationship between inequality and income per capita remains negative in this graph.

Figure 8 shows the relationship between economic complexity and income per capita. Figure 8a includes all states, and the relationship is not clear. In Figure 8b, data for the state of São Paulo and the federal district are omitted. Figure 8b indicates that the higher the ECI level, the higher the dispersion in GDP per capita between states.

[Figure 6] ABOUT HERE

[Figure 7] ABOUT HERE

[Figure 8] ABOUT HERE

4 Data & Methodology

4.1 Data Description

The data used in our paper was collected from several sources, all consisting of Brazilian government entities or government-led institutes. Table 9 in Appendix I presents summary statistics for the variables employed.

Our indicator of economic complexity is the ECI, a measure of the complexity of a region's economy, which is calculated by taking the average complexity of the products a region exports with international comparative advantage, weighted by the share of overall exports for that location. In turn, product complexity is based on the concepts of diversity (the number of products the region exports with comparative advantage) and ubiquity (the number of regions that export a given product with comparative advantage). The main underlying idea is that more complex products are produced and exported by a more limited number of regions and require more productive knowledge. A high level of ECI is therefore related to more complex products which are produced by few regions that produce different products (see Hidalgo and Hausmann (2009) and Hausmann et al. (2014b)).[5] The ECI data originates from the Secretariat of Foreign Trade (SECEX) and was downloaded through the DataViva visualization tool, a large platform which provides official social and economic data for Brazil at several regional levels.

As dependent variables, two different indicators of inequality are used: the Gini and the Theil indices. The Institute of Applied Economic Research (IPEA), a government-led research organization, provides data for both indicators. In addition, a second dataset for the Gini coefficient originating from RAIS (downloaded through DataViva) is used as a robustness check.

Our definition of income is GDP per capita, measured in 2010 Brazilian Reais. This data originates from the Institute of Geography and Statistics (IBGE), the government agency responsible for official collection of statistical data. The size of the population for each state was also estimated by the IBGE.

Data on the share of the population self-declared "white" and on the share of informal workers originates from the Continuous National Household Sample Survey (PNAD), conducted yearly by the IBGE. For the share of informal workers, there are three different definitions available. Since all definitions yielded the same results when included in our models (as Table 10 in Appendix II demonstrates), we employed the most conservative definition in our main models.[6]

We consider two different measures of educational attainment. First, data on the

[5]http://legacy.dataviva.info/en/about/glossary/complexity/

[6]Our definition of informality corresponds to "Grau de Informalidade Definição III": (Workers Without Contract + Self-Employed) / (Protected Workers + Workers Without Contract + Self-Employed + Employers).

share of individuals in each state by years of schooling was obtained from the PNAD. Based on this data and following Castilho et al. (2012), we constructed three different education categories: unskilled (less than 4 years of education), semi-skilled (from 4 to 10 years), and skilled (11 or more years). In addition, we alternate this with data on total average years of schooling of people aged 25 years or more, collected by IPEA, which provides a larger number of observations, and is the educational variable used by Hartmann et al. (2017a).

To measure the share of the agricultural sector, we constructed the ratio of the number of jobs in the Agriculture and Animal Farming sector as a share of total jobs covering all industry sectors for each state. To do so, we used industry data organized by sector from DataViva. In addition, to capture the rate of urbanization, we use the share of economically active population (PEA) in an urban situation.

As international trade data, we use the value of exports and imports from SECEX (obtained through DataViva). We constructed imports and exports as a share of output using data on total GDP at constant prices, measured in 2010 Reais.[7]

Finally, we use government expenditure on science and technology in each state as a proxy for technological development. This data comes from the National Treasury Secretariat, part of the Ministry of the Economy.

4.2 Econometric Specification

Our methodology follows two existing papers closely. The first one is by Hartmann et al. (2017a), which is our reference for linking economic complexity and inequality. The second one is the paper by Castilho et al. (2012), which provides the relevant methodology for researching the case of Brazil at the state level.

Our research is carried out at the state level, covering Brazil's 27 federative units (26 states and one federal district) for the period 2002-2014. The time scope of the study is determined by data availability of the ECI index and the regional depth level is determined by the availability of the inequality indices. The following regression is our main structural form:

$$y_{it} = \alpha_i + \beta_1 ECI_{it} + \beta_2 ECI_{it}^2 + \beta_3 \ln(GDPpc)_{it} + \beta_4 \ln(GDPpc)_{it}^2 + \boldsymbol{X'}\gamma + \epsilon_{it} \quad (1)$$

y_{it} is our main dependent variable and denotes income inequality, measured by either the Gini or the Theil indices. ECI_{it} and ECI_{it}^2 denote our main independent variables of interest, the economic complexity index and its square term. Similarly, we also include the log of GDP per capita and its square as a main control variable. This allows us to test for the presence of the Kuznets curve in our data, and to see

[7]Since the value of imports and exports was in current US Dollars, we used a deflator and converted the currency into Reais. Data for the deflator originated from the World Bank and data on the official exchange rate was provided by the International Monetary Fund (IMF).

whether including the ECI affects the shape of the Kuznets curve, as was the case in the findings by Hartmann et al. (2017a). α_i denotes state-specific effects and ϵ_{it} denotes the error term.

$\boldsymbol{X}'\gamma$ denotes a vector of the control variables included in our regression analysis. The variables included are the following. The share of individuals self-declared "white" is included to account for ethnic inequalities. We expect a higher share of individuals self-declared "white" to be associated with a higher level of inequality, as is the case in Castilho et al. (2012). The share of informal workers and the share of the agricultural sector in each state are included as they have both been identified as determinants of income distribution in Brazil (Castilho et al., 2012). We expect a higher share of informal workers to be associated with higher inequality. From the findings by Castilho et al. (2012), the size of the agricultural sector does not appear to have an impact on inequality, but had a positive significant impact on poverty and thus is included for robustness.

The level of education covers the role of educational inequalities and we use both average years of schooling, and the share of skilled and semi-skilled workers alternately. We expect higher education levels to be associated with decreases in inequality. The log of population[8] is included to account for the dimension of the different states; a higher population is expected to lead to higher inequality, as Hartmann et al. (2017a) find. Exports and imports as a share of output are included to control for the effect of trade openness. In line with the findings by Castilho et al. (2012), a higher export ratio is expected to lead to lower inequality, while the impact of a higher import ratio is unclear (no significant results).

Finally, government expenditure in science and technology is used as a proxy for technological development, as this has been found to impact inequality in developing countries (Esquivel and Rodríguez-López (2003), Attanasio et al. (2004)). Higher technological development is expected to lead to higher inequality.

Similarly to Castilho et al. (2012), who tested for the relationship between trade liberalization and inequality in rural and urban areas, we assess whether the relationship between economic complexity and income inequality differs between rural and urban areas. To this end, we conducted this regression analysis separately for states which are 'mainly rural' and 'mainly urban'.

To separate the two groups of states, we used agricultural population as a share of total population for the year 2010[9], using data from the IBGE. Brazil as a whole has a high urbanization rate (the share of urban population reached 85.7% in 2015 (World Bank, 2017b)). Additionally, none of its states are predominantly rural.

[8]See footnote 12.

[9]This is the most recent year for which data on urban, rural and total population is available at the state level.

Consequently, states which had more than 25% of their population in rural areas were considered rural[10], while all other states were considered urban for the purpose of this analysis.

4.3 Methodology

We undertook the following procedure to define the estimation method in our analysis. We ran our regression using the First Differences estimator and conducted a Breusch-Godfrey test. -0.5 was comprised in the 95% confidence interval of the lagged residual, meaning that the error term is independent and identically distributed (i.i.d.), thus the Fixed Effects estimator is preferred to First Differences. Following this, we ran our regression using Fixed Effects and Random Effects, and conducted the Hausman test. The results suggest that the null hypothesis (of zero correlation between state-specific effects and the explanatory variables) can be rejected at the 1% significance level and thus Fixed Effects is preferred to Random Effects.

Fixed Effects was preferred to both First Differences and Random Effects and thus was used to carry out our research. In addition, Pooled OLS is also used to relax the assumption of strict exogeneity in all explanatory variables. As Table 9 in Appendix I shows, most of the variation observed in our variables consists of between (i.e. cross-sectional) variation[11], therefore Pooled OLS is particularly appropriate for our analysis.

The Breusch-Godfrey test for autocorrelation was conducted for these two estimators, which indicated the presence of autocorrelation, at the 1% significance level. The cluster option, which corrects for both autocorrelation and heteroskedasticity, was therefore used in all our regression estimations and robust standard errors are reported.

5 Results

This section outlines our regression analysis results. We start by outlining results according to the estimator used, namely Pooled OLS and Fixed Effects, and subsequently look at whether the results differed between rural and urban states. We present two main models. First, our baseline model which is based on the paper by Hartmann et al. (2017a), and includes the ECI and its square, the log of GDP per capita and its square, average years of schooling and the log of population. Second, an extended model which includes additional control variables relevant to the case

[10] Acre, Alagoas, Bahia, Maranhão, Pará, Piauí, Rondônia, and Sergipe.

[11] This can be explained by the fact that our data only spans 13 years and that, by nature, our variables tend to move slowly over time.

of Brazil, following those employed by Castilho et al. (2012).

5.1 Pooled OLS

Table 1 shows the estimation results for our baseline model using Pooled OLS. The results suggest an inverted U-shaped relationship between the ECI and inequality. In contrast, the coefficients on $\ln(GDPpc)^2$ point to a U-shaped relationship between income per capita and inequality. Average years of schooling have a statistically significant negative impact on inequality, meaning higher average years of education are associated with lower inequality. These results hold for both the Gini and the Theil indices. The log of population does not explain changes in inequality over this time period (the coefficient only becomes statistically significant when the ECI is omitted from the model, and this is only true in the case of the Gini coefficient). In terms of explanatory power, the biggest drop in the adjusted R-squared is observed when GDP per capita is omitted from the model, followed by the ECI.

Table 2 presents our analysis with the extended model. The results with respect to the ECI and the log of GDP per capita remain the same – there is an inverted-U shaped relationship between the ECI and inequality and a U-shaped one between the log of GDP per capita and inequality. Similarly, the impact of education, now measured by the share of skilled and semi-skilled workers in each state, remains the same – higher education levels are associated with lower inequality. The imports and exports shares are both associated with lower inequality levels, whereas a larger agricultural sector leads to higher inequality. A higher share of informal workers is sometimes associated with higher inequality, but the statistical significance of the coefficients disappears once more control variables are included. Finally, the share of individuals self-declared "white" and the urbanization rate are not statistically significant predictors of inequality.

[Table 1] ABOUT HERE

[Table 2] ABOUT HERE

5.2 Fixed Effects

Table 3 presents the results of our baseline model using Fixed Effects. The results suggest that there is an inverted U-shaped relationship between the ECI and inequality, but the statistical significance levels are lower than those observed with Pooled OLS. With respect to income per capita, there is a downward-sloping linear relationship in the case of the Theil index, and this relationship becomes U-shaped when the ECI is omitted from the regression (in the case of the Gini coefficient, the estimation results are never statistically significant). There is a negative effect of average years of schooling on inequality, which is only statistically significant when the log of GDP per capita is omitted. There is no effect of the log of population on inequality levels; however, its inclusion in the regression equations impacts the statistical significance of the other explanatory variables.

Table 4 shows the estimation results with respect to our extended model. As before, the relationship between the ECI and inequality remains inverted U-shaped. The relationship between the log of GDP per capita and inequality changes depending on the specification – there is a downward-sloping linear relationship in some regression equations, and a U-shaped relationship in others. When all control variables are included, there is a negative linear relationship between income per capita and the Theil index only. The share of skilled workers now has a positive impact on inequality level when all control variables are included. The share of individuals self-declared "white" and the share of informal workers are associated with increases in inequality; whereas the urbanization rate and, to a lesser extent, the export share are associated with decreases in inequality. The size of the agricultural sector, and the imports share have no impact on inequality.

[Table 3] ABOUT HERE

[Table 4] ABOUT HERE

5.3 Rural and Urban Areas

To estimate whether these results differ significantly between rural and urban areas, we conducted the same analysis while separating states into two groups based on whether they are 'rural' or 'urban'. Tables 5 and 6 show these results for Pooled

OLS and Fixed Effects estimators respectively. The results in this section changed significantly based on the estimator employed.

With Pooled OLS (Table 5), the effects described in Section 5.1 seem to apply only to urban states, where there is an inverted U-shaped relationship between the ECI and inequality and a U-shaped relationship between the log of GDP per capita and inequality. In addition, the estimation suggests a negative impact on inequality from all education variables, and a positive one from the log of population and the share of the agricultural sector. With respect to the rural states, the only statistically significant variable is the share of semi-skilled workers, which has a negative effect on inequality.

In the case of Fixed Effects (Table 6), the results suggest that the ECI has no effect on inequality in either rural or urban states and that the log of GDP per capita presents a U-shaped relationship with inequality in rural states only. In terms of control variables, there is a positive effect of the share of skilled and semi-skilled workers and of informality on inequality in rural states, and a positive effect of the share of individuals self-declared "white" and informality on inequality in urban states.

To check whether these results might be influenced by the small number of observations for the case of rural states, we used an alternative definition of 'rural' and 'urban' states. States were considered 'rural' if 20% of their population or more was in a rural situation (as opposed to the previous 25%) – and conducted the same analysis. The results using this alternative definition were similar to the ones presented here with respect to both estimators.

[Table 5] ABOUT HERE

[Table 6] ABOUT HERE

6 Robustness Checks

6.1 Excluding Outliers

The first robustness check excludes the two outliers identified in Section 3, namely São Paulo and the federal district. Appendix III presents all tables related to this analysis. In the extended model, we find an inverted U-shaped relationship between the ECI and inequality. With respect to income per capita, however, the relationship is not evident once data for the outliers is omitted. In some specifications, there is a negative linear relationship between income per capita and inequality. The relationship between education levels and inequality remains similar as before in both the baseline and extended models. On the other hand, the log of population gained statistical significance (in the baseline model with all variables included) and a higher population size is associated with higher inequality levels. All other control variables are no longer statistically significant predictors of inequality.

Tables 13 and 14 show the same analysis for the case of Fixed Effects. The main difference lies in the relationship between the ECI and inequality, which is now nonexistent when control variables are included in the baseline model and in all specifications in the extended model. On the other hand, GDP per capita now presents a U-shaped relationship with inequality in both the baseline and extended models. The coefficient signs and statistical significance levels of our control variables remain similar to those found while including the outliers.

The same was done for our analysis separating rural and urban states. Tables 15 and 16 present these results. With respect to Pooled OLS (Table 15), there is a change in the impact of the ECI, which only appears to have an upward sloping linear relationship with inequality in urban states. Similarly, the impact of income per capita is also not apparent in these results. Nevertheless, with respect to the other control variables, the results are similar to those found in the regression equations including all states. In the case of Fixed Effects (Table 16), there are no significant alterations. There is still a positive linear relationship between the ECI and inequality, and a U-shaped relationship between the log of GDP per capita and inequality in rural states. Similarly, the conclusions related to the control variables do not change with the exclusion of outliers.

6.2 Alternative Gini Dataset

The second robustness check consists of using an alternative Gini dataset (originating from RAIS). Appendix IV presents all tables related to this robustness check. Tables 17 and 18 present the results for the case of Pooled OLS. The baseline model shows similar results to those found with the other inequality measures, with the exception of schooling, which now has no impact on inequality. With respect to the extended model, the inverted U-shaped relationship between the ECI and inequality, and the U-shaped one between the log of GDP per capita and inequality are still apparent in some specifications, but do not hold when all the control variables are included. The control variables are now all statistically significant predictors of inequality, with the exception of the imports share. As before, education levels and the exports share are associated with lower inequality levels. In addition, the share of individuals self-declared “white” now has a statistically significant negative association with inequality. Similarly, the share of the agricultural sector, which was previously associated with higher inequality, now shows a negative relationship with inequality. Finally, informality and urbanization show a positive relationship with inequality.

The results of the same exercise using Fixed Effects are presented in Tables 19 and 20. These estimations do not show any relationship between the ECI and inequality, and the relationship between the log of GDP per capita and inequality is now U-shaped (compared to the linear negative relationship previously observed with the Theil index). This is the case in both the baseline and the extended model. With respect to control variables, there is a positive impact on inequality from the share of individuals self-declared “white” and a negative one from the share of exports. All other control variables are not statistically significant predictors of inequality.

Tables 21 and 22 show similar results while separating between urban and rural states. In the Pooled OLS estimation, the ECI follows a statistically significant inverted U-shaped relationship with inequality in urban states and this is only observed in the baseline model. The same holds for a statistically significant U-shaped relationship between GDP per capita and inequality. With respect to the control variables, there are some differences too, as more of the control variables present statistically significant results in both rural and urban states compared to the analysis with the other inequality measures.

In the Fixed Effects estimation, the ECI is only statistically significant in the case of urban states, where there is a negative linear relationship in both models. In addition, the results show a linear downward-sloping relationship between the log of GDP per capita and inequality in the baseline model, and a U-shaped relationship in the extended model in urban states. The share of exports impacts inequality negatively in urban states. With respect to the rural states, the model does not provide any strong predictors of inequality.

6.3 Industry and Occupation Diversity

Our third and final robustness check investigates whether specific features of the Brazilian economy, coupled with the way the ECI is measured, are affecting our results. In order to check if this is the case, we looked for alternative indicators which relate to the productive structure and the economic complexity of a region but are not measured with trade data, and used them as a robustness check. To this end, we looked at industry and occupation diversity.

Brazil is divided into five geopolitical regions: North, North-East, Center-West, South-East and South, accounting for 26 states and one federal district. The distribution of economic activity across regions differs a lot by industries. For example, chemicals are mainly produced in the state of Bahia (North-East region), whereas transportation industries are mostly located in the state of São Paulo (South-East region) (Fally et al., 2010). More generally, manufacturing industries are concentrated in the South-East region, while agriculture, although more evenly distributed geographically, is the main source of income of the Centre-West states (Filho and Horridge, 2005). Similarly, exports are also geographically concentrated. In fact, Castilho et al. (2012) highlight the strong geographical concentration of exports and imports as an important feature of the Brazilian case. More specifically, in 2004 only three states (São Paulo, Minas Gerais and Rio Grande do Sul) accounted for more than 50% of total exports, while 20 states had less than 5% share of total exports (Castilho et al., 2012). Since then, this situation has not changed significantly.

As described in Section 4.1, the ECI is measured with international export data and takes international comparative advantage into account. However, since Brazil is a large country, it is likely that international export data for a state does not fully reflect the entirety of production undertaken in that state. For instance, some production might target the domestic market only. When this is the case, the ECI index will not fully capture the level of economic complexity in a given state.

This might be a problem if, in some states, production is focused on very different industries and the difference in the level of complexity between those industries is large – for example, a state producing highly complex products for the domestic market, while producing goods involving lower complexity for the international market. This argument could explain, for example, why the state of Santa Catarina (South region) had simultaneously the lowest level of economic complexity (and of inequality), while having a relatively high level of income per capita in 2014.

Industry diversity is measured by the number of unique industries present in a given state, based on the National Classification of Economic Activity (CNAE). Occupation diversity is the number of unique occupations present for a given state, based on the Brazilian Classification of Occupations (CBO). These variables were chosen because, unlike the ECI, their measurement does not depend on export data and thus provides an overlook of total production in a state, including production for the domestic market, which is not accounted for in the case of the ECI.

Figures 9a and 9b show the relationship between the ECI and occupation and industry diversity respectively, for each state (averaged from 2002 to 2013). In both figures, the outlier refers to the state of São Paulo, which has a much higher ECI than all other states. An interesting feature in these plots is the fact that states have very different levels of industry and occupation diversity regardless of their level of economic complexity. In addition, many states with ECI close to zero have high levels of occupation and industry diversity.

[Figures 9a and 9b] ABOUT HERE

[Figures 10a and 10b] ABOUT HERE

Figures 10a and 10b plot the evolution of industry and occupation diversity over time and show that trends in both variables follow a very similar path in all states. The dispersion between states remains the same across the time period between 2002 and 2013, with no signs of convergence or divergence between states. There is a sudden increase in both industry and occupation diversity similar across all states, which is likely a result of changes in their definition or measurement.

When looking at occupation and industry diversity, São Paulo and Santa Catarina are very similar. For instance, in 2013, industry diversity was 665 in São Paulo and 637 in Santa Catarina, and occupation diversity was 598 and 591 respectively. These levels of diversity are also amongst the highest across all states. This is striking, given the substantial difference observed in the ECI between São Paulo, the state with the highest ECI level, and Santa Catarina, the state with the lowest one.

Tables 7 and 8 show the regression analysis results including industry and occupation diversity in our baseline model, using Pooled OLS and Fixed Effects respectively. In the case of Pooled OLS, the results are not affected by the addition of these variables. After including these two indicators, the estimated coefficients still point to an inverted-U shaped relationship between the ECI and inequality, a U-shaped relationship between the log of GDP per capita and inequality, and a negative relationship between average years of schooling and inequality. The only change observed is that the log of population now has a positive impact on inequality in two of the specifications (and only at the 10% significance level). Both industry and occupation diversity are associated with lower inequality levels (with the exception in the case of the Theil index, which is not impacted by industry diversity). When the ECI is omitted from the regression equations, the negative relationships between industry and occupation diversity remain as before. All other control variables have similar coefficients and statistical levels. The adjusted R-squared decreases.

In the case of the Fixed Effects estimator, as before, including these two variables does not affect our conclusions. There is no impact of the ECI on inequality, and there is a negative linear impact of the log of GDP per capita on inequality, which only holds for the Theil index. The control variables are not significant predictors of inequality. In this case, only occupation diversity shows a statistically significant negative impact on inequality, which remains similar after the ECI is omitted from the regression equations. For some specifications, the adjusted R-squared increases after the omission of the ECI, whereas it decreases in others.

Overall, our results are robust to the inclusion of an alternative measure of the productive structure in a state. The inclusion of industry and occupation diversity in our regression equations does not impact our main conclusions with respect to the relationship between the ECI and inequality.

[Table 7] ABOUT HERE

[Table 8] ABOUT HERE

7 Discussion

7.1 Implications of Results

Overall, we conclude that there is an inverted U-shaped relationship between the ECI and income inequality, observed in both estimation methods. This relationship is robust to the exclusion of outliers; the use of alternative inequality measures in the case of Pooled OLS; and the inclusion of an alternative measure of the productive structure of states in our baseline model.

This inverted U-shaped relationship between the ECI and inequality represents a developmental Kuznets curve. This indicates that, as economic complexity in a state increases, the inequality level first increases, and later decreases. This result is in line with our initial hypothesis and differ from those by Hartmann et al. (2017a), who test for a linear relationship between the ECI and inequality and find that the ECI is a negative predictor of inequality. While they include the square of GDP per capita to test for a quadratic relationship, the authors do not do the same for the ECI. Given that GDP per capita has been criticized for not accurately reflecting the level of development and welfare in a country (in fact, Simon Kuznets was himself aware of the drawbacks of GDP as a measure of a country's welfare and warned the government about these in 1934), it is beneficial to test for a quadratic relationship between the ECI and inequality and see if the phenomenon described by the idea of the Kuznets curve is observed with respect to economic complexity.

In the case of income per capita, such a relationship was indeed not present. Rather, there appears to be a U-shaped relationship in some cases, and a linear negative relationship in others, with inequality. This relationship is an inverted Kuznets curve, whereby higher development levels are initially associated with decreases in inequality and later with increases. We suspect this is a cross-sectional relationship, rather than a time series one and that it appears due to some states with very high incomes also having a high inequality level. These results do not coincide with those by Hartmann et al. (2017a), who found an inverted-U shaped relationship nor with those by Castilho et al. (2012), who only include GDP growth rate and do not find a significant relationship between this variable and inequality. In addition, we found no impact on the relationship between GDP and inequality from the inclusion or exclusion of the ECI from the baseline model, something which Hartmann et al. (2017a) highlighted as a striking aspect in their findings.

Finally, with respect to our control variables, the educational variables and the imports and exports shares are associated with lower inequality levels, whereas the share of individuals self-declared "white" and the share of informal workers are associated with higher inequality levels. The effects of population size, the size of the agricultural sector and the urbanization rate on inequality are ambiguous, presenting sometimes a positive, negative or no relationship at all. These results hold across most of our models and are in line with our hypotheses and the findings by Castilho et al. (2012).

As for our analysis looking at rural and urban states separately, the results are ambiguous. In the case of Pooled OLS, we found a much larger predictive power of the ECI (and the overall model) in urban states than in rural ones (where none of the variables were statistically significant). This might indicate that the underlying processes behind inequality significantly differ between rural and urban areas. A possible implication of this might be that industrial policy is more effective in tackling inequality in urban areas, whereas other policies might be necessary in rural areas. When using Fixed Effects, however, the conclusions differed significantly from this and the ECI was not a statistically significant predictor of inequality in either rural nor urban states.

7.2 Economic Complexity Index

As described in the motivation for our robustness check in Section 6.3.1, the ECI is a measure of economic complexity constructed with export data that explicitly accounts for the international comparative advantage of a region.

The dispersion between the level of income per capita and the ECI observed in some states reflects precisely the fact that the ECI takes into account international competitiveness. A clear example of this is the case of São Paulo and Santa Catarina. Despite having similar levels of income per capita, inequality and industry and occupation diversity, these two states differ a lot in their economic complexity levels

– with São Paulo having the highest, and Santa Catarina the lowest, ECI levels of all states in 2014.

Since we control for GDP per capita and other variables that take into account that some production within states targets only the domestic market – and that income originates from this production – this does not present a major drawback in our paper. Rather, a consequence of this is that our results imply that international competitiveness is important for regions, and that it gives them an opportunity to lower inequality levels in the long run.

If an alternative way of measuring the ECI becomes available which does not depend on export data – but rather quantifies the productive structure of states regardless of their orientation towards the domestic or the international market – it will be possible to study how economic complexity affects inequality within a country independently of international outlook and comparative advantage. This would be a particularly relevant analysis for Brazil, where the domestic market is large and has an important contribution to the economy (Filho and Horridge, 2005).

8 Conclusion

In this paper we looked at how economic complexity affects income inequality within Brazil. We analyzed the 27 Brazilian states, from 2002 to 2014, using panel data analysis. Our main proposition that a country's economic complexity affects regional wage differentials in a nonlinear way was confirmed. More specifically, our results point to an inverted U-shaped relationship with inequality.

As a possible explanation, we hypothesize that, as economic complexity increases, the demand for knowledge also increases, leading to a higher demand for skilled labor, thus increasing the dispersion between skilled and unskilled workers' wages, causing higher inequality. However, once a certain level of economic complexity is attained, returns to higher education levels may decrease, which would lower wage differentials between skilled and unskilled workers' wages.

A central implication of this finding is that industrial policy, despite having an initial cost of higher inequality, can lead to lower inequality in the long run. In this respect, governments – either at the federal or at the state level – should strive to improve economic complexity, raise education and human capital, and enable more interaction and learning between workers, in order to ensure more inclusive and sustainable future growth.

This paper contributes to the literature on inequality in Brazil, a topic that is far from being settled, as economists still try to further understand the underlying determinants of inequality in one of the most unequal countries in the world. In addition, it contributes to the more general literature on the determinants of inequality. There are still gaps in this literature, particularly related to the possible links between productive structures and inequality, as an adequate measure of productive structure was lacking until recently. Finally, by studying this question within a large country, rather than across countries, and by testing for a quadratic relationship, it offers further insights to the literature on the ECI and on how it relates to income inequality.

Further research should look into expanding the time frame analyzed and regional depth level, expanding the control variables used to include those for which data was poor or missing, as well as using (or developing) a measure of the ECI that does not depend on international export data, but accounts for full production within a state.

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Figures

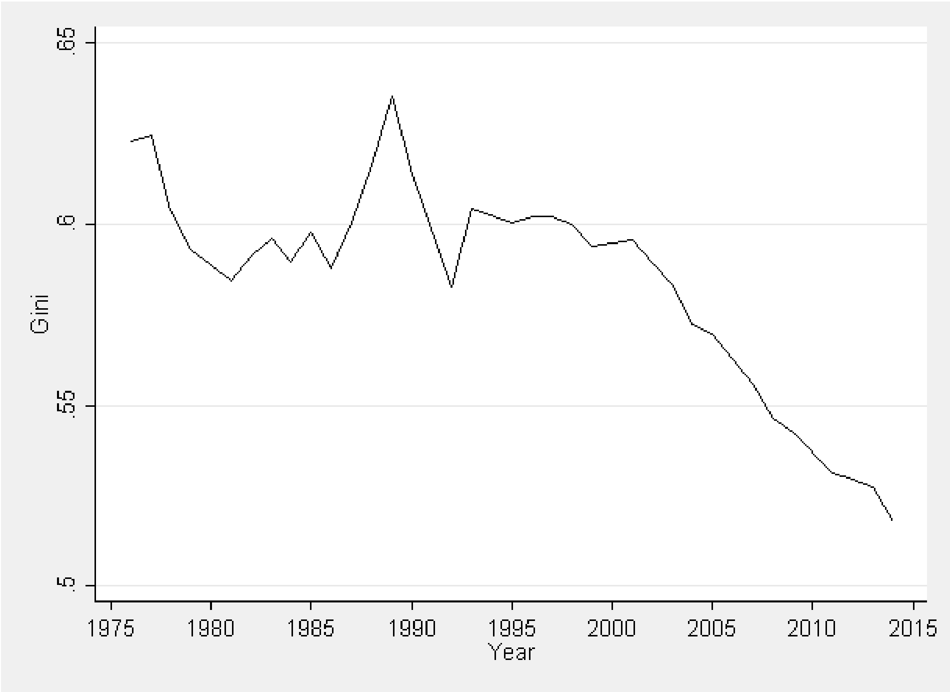


Figure 1: Gini Coefficient for Brazil, 1976 to 2014.

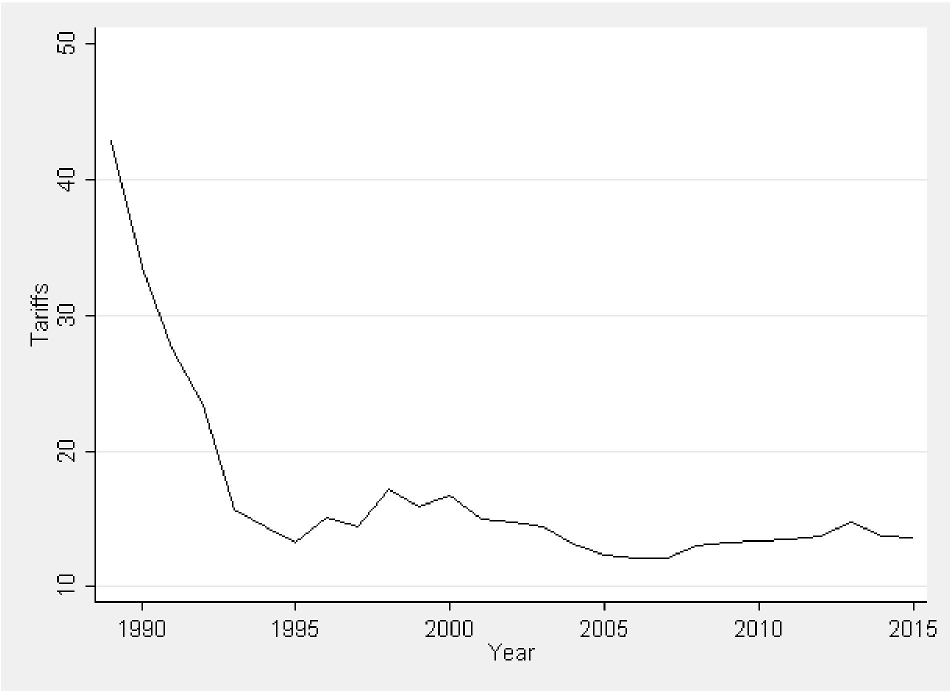
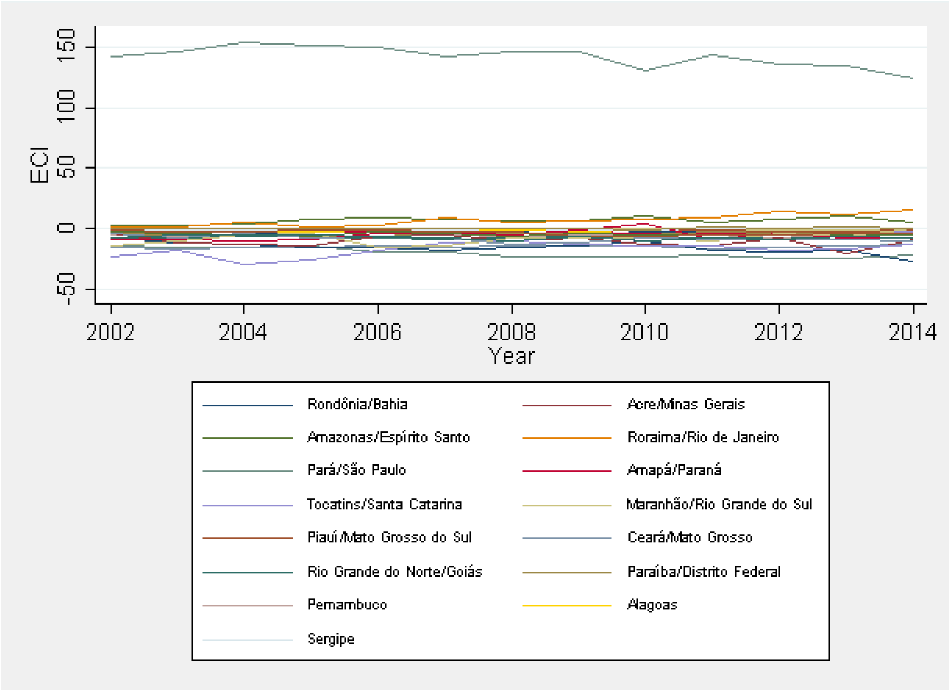
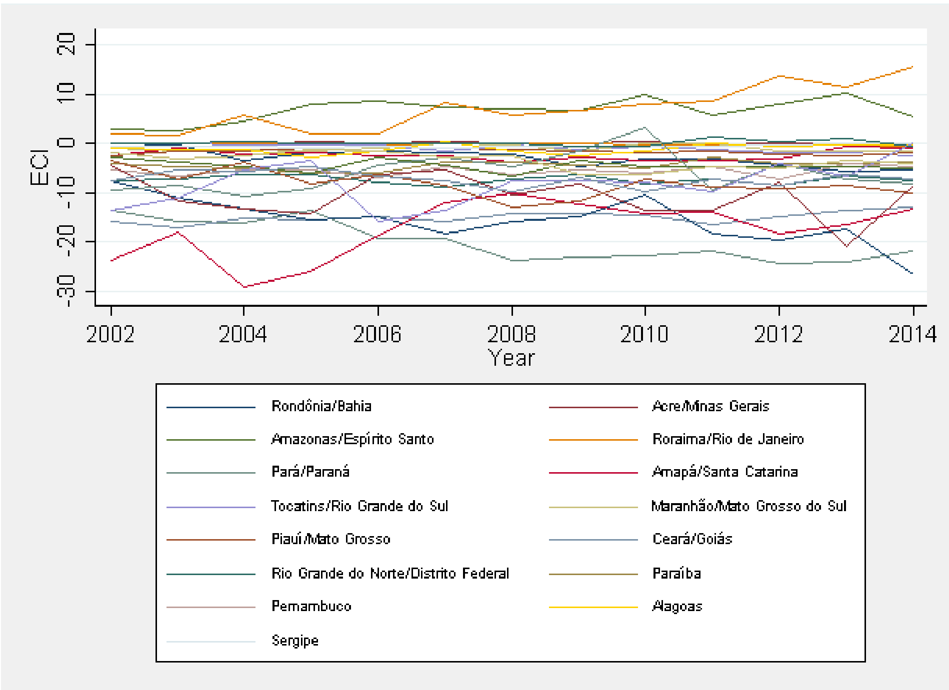


Figure 2: Trade Liberalization in Brazil. Simple mean applied tariff, 1989 to 2015.

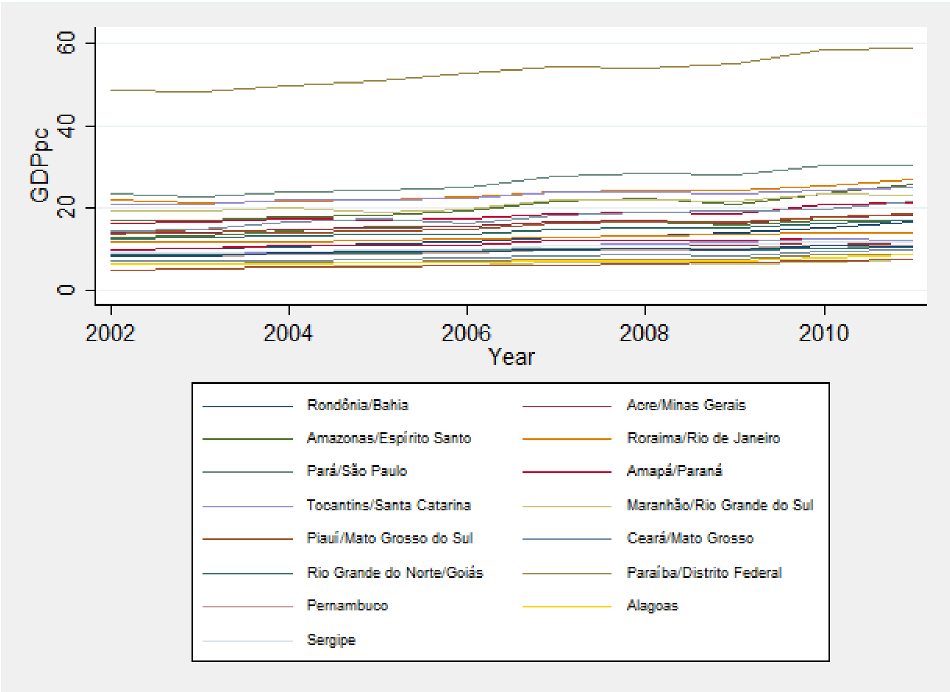


(a) Including all states



(b) Excluding the state of São Paulo

Figure 3: Economic Complexity Index for Brazilian States, 2002 to 2014.



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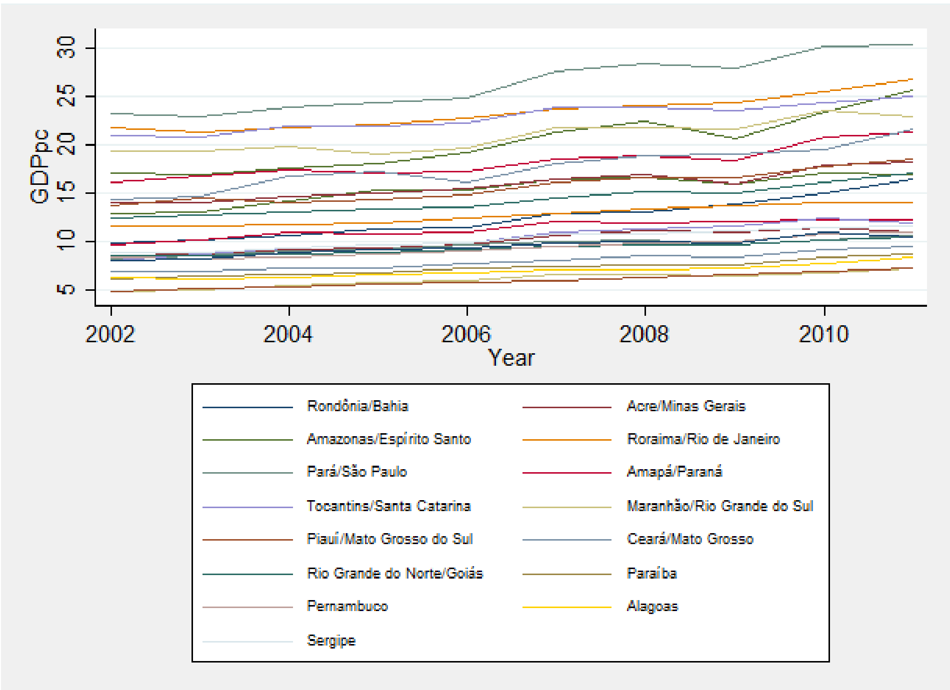


(b) Excluding the Federal District

Figure 4: Income per capita for Brazilian States, 2002 to 2011.

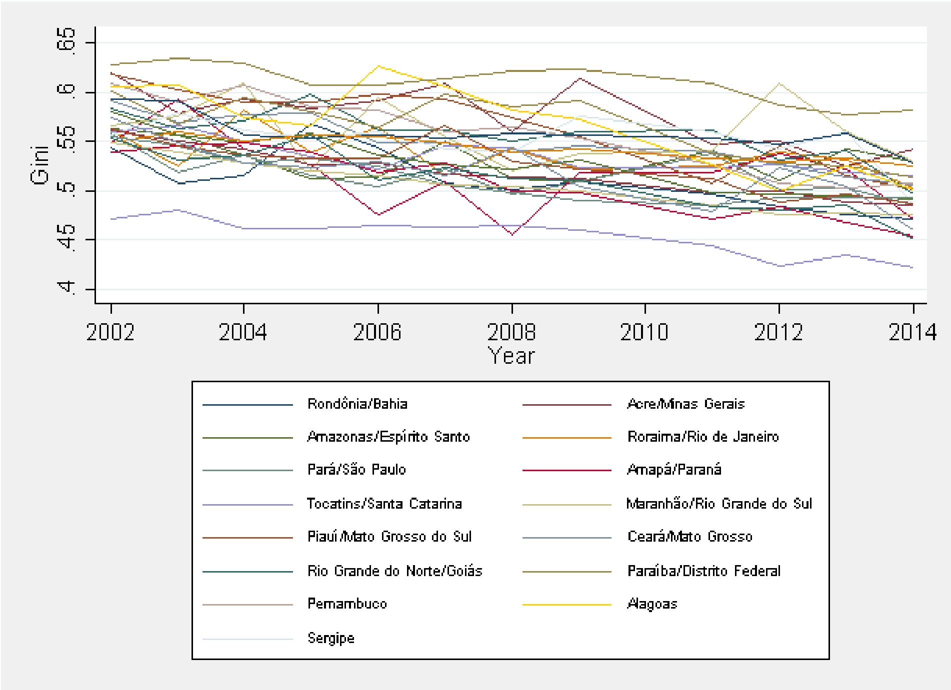
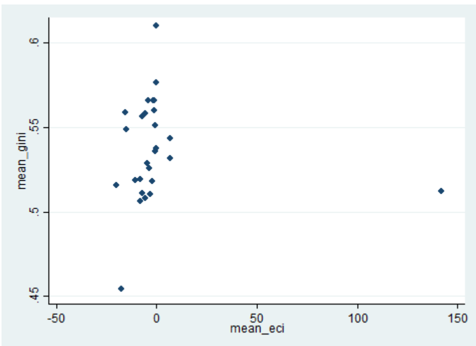
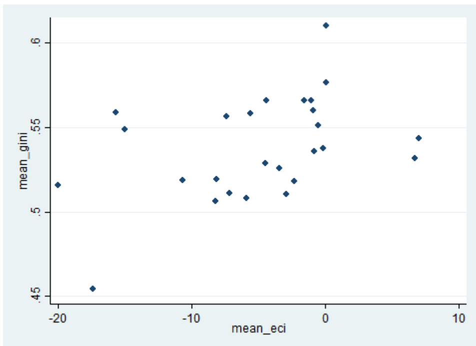


Figure 5: Gini Coefficient for Brazilian States, 2002 to 2011.

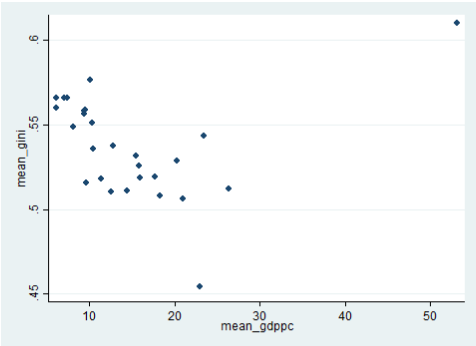


(a) Including all states

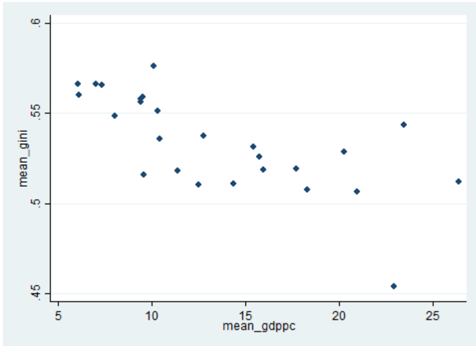


(b) Excluding the state of São Paulo

Figure 6: Scatter plots of the relationship between inequality and economic complexity, averages from 2002 to 2014.

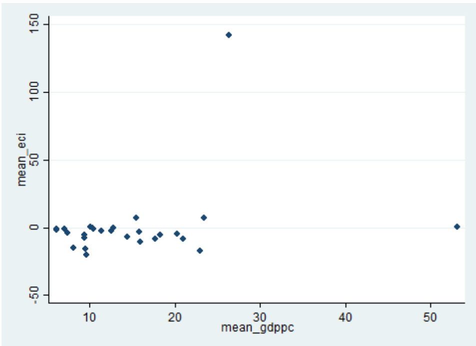


(a) Including all states

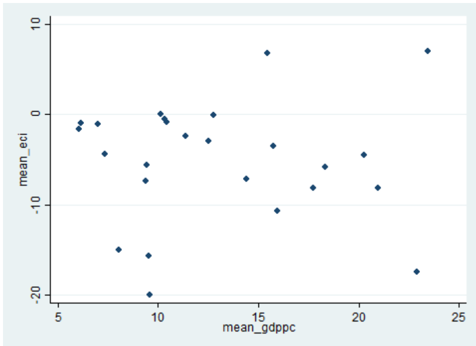


(b) Excluding the federal district

Figure 7: Scatter plots of the relationship between inequality and income per capita, averages from 2002 to 2014.

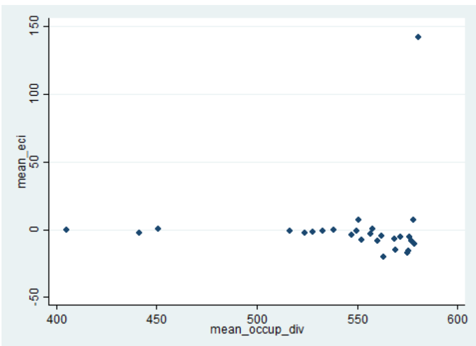


(a) Including all states

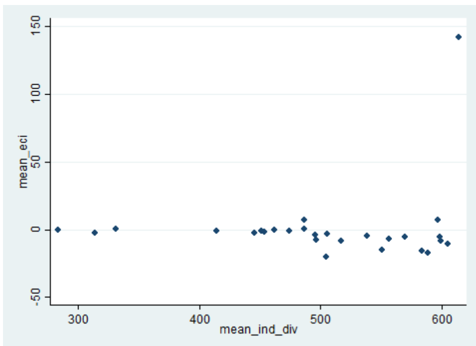


(b) Excluding São Paulo and federal district

Figure 8: Scatter plots of the relationship between economic complexity and income per capita, averages from 2002 to 2014.

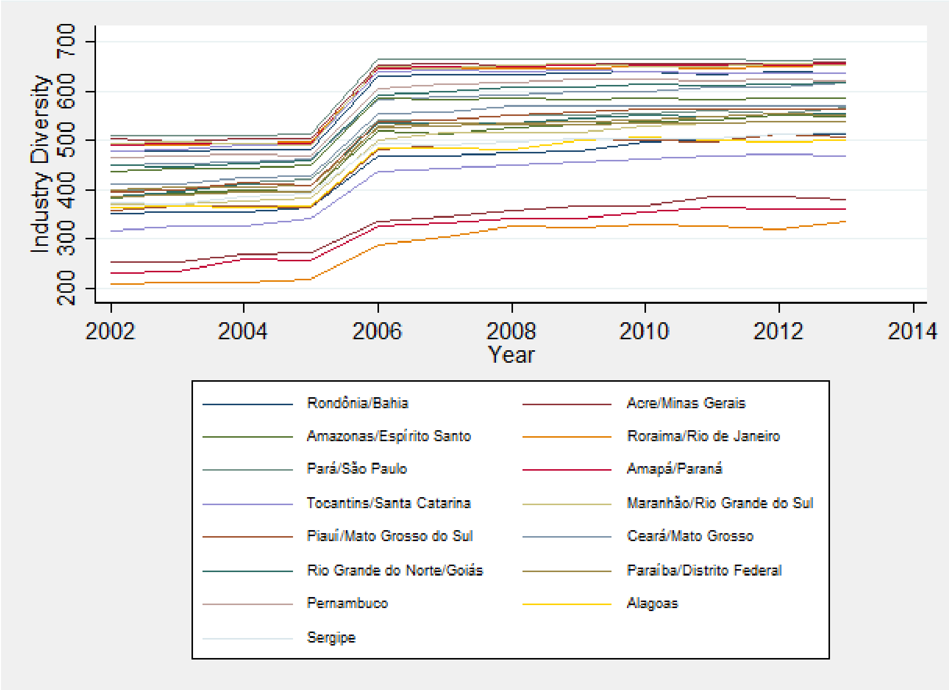


(a) Occupation Diversity

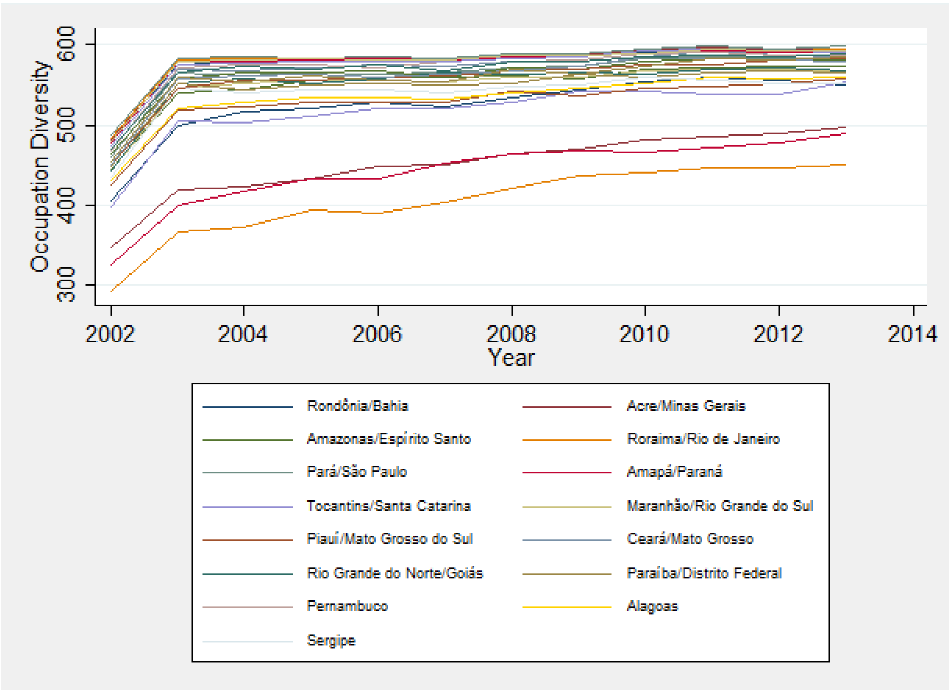


(b) Industry Diversity

Figure 9: Relationship between the ECI and occupation and industry diversity for all Brazilian states, averages from 2002 to 2013



(a) Industry Diversity



(b) Occupation Diversity

Figure 10: Evolution of industry and occupation diversity for all Brazilian states, averages from 2002 to 2013

Tables

Table 1: Baseline Model, Pooled OLS

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ECI	0.00146*	0.00310	0.00129**	0.00259**	0.00161***	0.00352***	0.00150**	0.00392***			0.00178***	0.00488***
	(0.000721)	(0.00184)	(0.000549)	(0.00125)	(0.000558)	(0.00121)	(0.000633)	(0.00126)			(0.000523)	(0.00107)
ECI^2	-1.17e-05**	-2.57e-05*	-9.83e-06**	-1.93e-05**	-1.21e-05***	-2.59e-05***	-1.11e-05**	-2.95e-05***			-1.28e-05***	-3.59e-05***
	(5.15e-06)	(1.32e-05)	(3.70e-06)	(8.47e-06)	(3.77e-06)	(8.20e-06)	(4.44e-06)	(8.91e-06)			(3.88e-06)	(8.06e-06)
$\ln(GDPpc)$			-0.320***	-0.900***	-0.262***	-0.729***	-0.261***	-0.733***	-0.295***	-0.821***		
			(0.0624)	(0.133)	(0.0665)	(0.139)	(0.0645)	(0.150)	(0.0611)	(0.144)		
$\ln(GDPpc)^2$			0.0553***	0.149***	0.0519***	0.139***	0.0522***	0.138***	0.0575***	0.152***		
			(0.0115)	(0.0233)	(0.0121)	(0.0237)	(0.0114)	(0.0253)	(0.0102)	(0.0231)		
$Schooling$					-0.0192***	-0.0563***	-0.0201***	-0.0530***	-0.0167**	-0.0446**	-0.0151*	-0.0536**
					(0.00365)	(0.0107)	(0.00426)	(0.0103)	(0.00653)	(0.0168)	(0.00861)	(0.0194)
$\ln(Population)$							-0.00210	0.00781	-0.00673*	-0.00515	-0.00104	0.0101
							(0.00412)	(0.00923)	(0.00342)	(0.00784)	(0.00349)	(0.00800)
Constant	0.546***	0.619***	0.997***	1.921***	0.995***	1.916***	1.028***	1.795***	1.119***	2.048***	0.662***	0.826***
	(0.00603)	(0.0167)	(0.0850)	(0.189)	(0.0862)	(0.182)	(0.0883)	(0.183)	(0.0879)	(0.195)	(0.0588)	(0.135)
Observations	324	324	243	243	243	243	243	243	243	243	324	324
R^2	0.095	0.058	0.477	0.506	0.526	0.558	0.528	0.561	0.463	0.506	0.283	0.341
Adjusted R^2	0.0896	0.0520	0.468	0.498	0.516	0.548	0.516	0.550	0.454	0.498	0.274	0.332

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Extended Model, Pooled OLS

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI	0.00125**	0.00261**	0.00111**	0.00254**	0.00116**	0.00245*	0.00137**	0.00287**	0.00127**	0.00262**	0.00136*	0.00280*	0.000978*	0.00246*
	(0.000548)	(0.00122)	(0.000445)	(0.00114)	(0.000502)	(0.00120)	(0.000551)	(0.00121)	(0.000538)	(0.00123)	(0.000719)	(0.00162)	(0.000510)	(0.00122)
ECI^2	-9.34e-06**	-1.88e-05**	-8.37e-06**	-1.89e-05**	-8.62e-06**	-1.80e-05**	-1.03e-05***	-2.12e-05**	-9.74e-06**	-1.95e-05**	-1.03e-05**	-2.08e-05*	-7.57e-06**	-1.86e-05**
	(3.73e-06)	(8.34e-06)	(3.02e-06)	(7.79e-06)	(3.40e-06)	(8.15e-06)	(3.70e-06)	(8.23e-06)	(3.64e-06)	(8.39e-06)	(4.85e-06)	(1.10e-05)	(3.44e-06)	(8.27e-06)
$\ln(GDPpc)$	-0.193***	-0.583***	-0.308***	-0.896***	-0.269***	-0.843***	-0.338***	-0.962***	-0.328***	-0.888***	-0.287***	-0.849***	-0.146***	-0.543***
	(0.0659)	(0.131)	(0.0594)	(0.143)	(0.0639)	(0.156)	(0.0680)	(0.150)	(0.0609)	(0.124)	(0.0538)	(0.136)	(0.0499)	(0.137)
$\ln(GDPpc)^2$	0.0422***	0.118***	0.0540***	0.149***	0.0500***	0.143***	0.0585***	0.161***	0.0561***	0.148***	0.0506***	0.142***	0.0348***	0.109***
	(0.0115)	(0.0216)	(0.0105)	(0.0242)	(0.0110)	(0.0249)	(0.0123)	(0.0260)	(0.0113)	(0.0224)	(0.00953)	(0.0230)	(0.00831)	(0.0217)
Skilled	-0.00491***	-0.0130***											-0.00441***	-0.0111***
	(0.00105)	(0.00227)											(0.000948)	(0.00251)
Semi-Skilled	-0.00254***	-0.00600***											-0.00398***	-0.00977***
	(0.000810)	(0.00180)											(0.000810)	(0.00222)
Share "White"			-0.000262	-6.73e-05									8.40e-07	0.000486
			(0.000281)	(0.000703)									(0.000301)	(0.000703)
Informality					0.00115*	0.00126							0.000410	0.000292
					(0.000635)	(0.00159)							(0.000591)	(0.00142)
Share Agric							0.116	0.421*					0.142*	0.477**
							(0.0807)	(0.217)					(0.0733)	(0.194)
Urbanization									0.000302	-0.000483			0.000644	0.000587
									(0.000389)	(0.00110)			(0.000424)	(0.00116)
Share Imports											-0.148**	-0.251	-0.0985*	-0.145
											(0.0680)	(0.176)	(0.0561)	(0.141)
Share Exports											-0.0675	-0.120	-0.0798*	-0.167*
											(0.0563)	(0.137)	(0.0388)	(0.0964)
Constant	0.930***	1.755***	0.983***	1.918***	0.834***	1.742***	1.015***	1.987***	0.994***	1.926***	0.955***	1.857***	0.830***	1.701***
	(0.0754)	(0.151)	(0.0804)	(0.197)	(0.116)	(0.304)	(0.0920)	(0.209)	(0.0855)	(0.194)	(0.0736)	(0.190)	(0.0751)	(0.192)
Observations	243	243	243	243	243	243	243	243	243	243	216	216	216	216
R^2	0.573	0.587	0.486	0.506	0.501	0.509	0.485	0.518	0.479	0.506	0.541	0.532	0.654	0.620
Adjusted R^2	0.562	0.577	0.475	0.495	0.491	0.499	0.474	0.508	0.468	0.496	0.528	0.519	0.633	0.598

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Baseline Model, Fixed Effects

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ECI	0.000566	0.00166	0.000147	0.000578	0.000259	0.000794	0.000249	0.000798			0.000298	0.00109
	(0.000801)	(0.00191)	(0.000302)	(0.00103)	(0.000317)	(0.00101)	(0.000313)	(0.00101)			(0.000306)	(0.000904)
ECI^2	2.47e-06	-1.46e-06	-1.96e-06*	-5.96e-06*	-2.09e-06*	-6.22e-06*	-1.43e-06	-6.53e-06			-2.34e-06*	-1.37e-05***
	(2.84e-06)	(6.90e-06)	(1.05e-06)	(3.34e-06)	(1.13e-06)	(3.39e-06)	(1.31e-06)	(4.22e-06)			(1.37e-06)	(3.78e-06)
$\ln(GDPpc)$			-0.114	-0.671***	-0.0873	-0.619***	-0.0879	-0.619***	-0.0933	-0.640***		
			(0.0690)	(0.189)	(0.0780)	(0.211)	(0.0814)	(0.211)	(0.0795)	(0.205)		
$\ln(GDPpc)^2$			-0.00741	0.0562	-0.00645	0.0581	-0.00532	0.0575	-0.00456	0.0608*		
			(0.0130)	(0.0344)	(0.0134)	(0.0344)	(0.0140)	(0.0350)	(0.0137)	(0.0339)		
Schooling					-0.00788	-0.0152	-0.00605	-0.0161	-0.00556	-0.0144	-0.0306***	-0.0812***
					(0.00668)	(0.0200)	(0.00680)	(0.0227)	(0.00665)	(0.0224)	(0.00649)	(0.0189)
$\ln(Population)$							-0.0359	0.0171	-0.0379	0.00856	-0.0283	0.0207
							(0.0448)	(0.163)	(0.0435)	(0.157)	(0.0552)	(0.159)
Constant	0.534***	0.599***	0.890***	1.957***	0.864***	1.908***	1.392**	1.657	1.426**	1.802	1.171	0.829
	(0.00200)	(0.00489)	(0.0912)	(0.259)	(0.0987)	(0.275)	(0.648)	(2.438)	(0.628)	(2.353)	(0.804)	(2.322)
Observations	324	324	243	243	243	243	243	243	243	243	324	324
R^2	0.007	0.003	0.460	0.328	0.467	0.330	0.469	0.330	0.468	0.329	0.530	0.307
Adjusted R^2	0.000967	-0.00327	0.451	0.316	0.456	0.316	0.456	0.313	0.459	0.318	0.524	0.298
Number of code	27	27	27	27	27	27	27	27	27	27	27	27

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Extended Model, Fixed Effects

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI	0.000151	0.000779	0.000256	0.000837	0.000206	0.000728	0.000184	0.000672	0.000171	0.000672	0.000344	0.00138	0.000314	0.00150
	(0.000298)	(0.00107)	(0.000294)	(0.00103)	(0.000299)	(0.00102)	(0.000302)	(0.00103)	(0.000319)	(0.00104)	(0.000393)	(0.00124)	(0.000363)	(0.00127)
ECI^2	-1.84e-06	-5.75e-06	-2.18e-06*	-6.50e-06*	-1.74e-06	-5.41e-06	-2.15e-06*	-6.46e-06*	-2.30e-06**	-7.27e-06**	-4.07e-06***	-1.07e-05***	-4.27e-06***	-1.22e-05***
	(1.09e-06)	(3.59e-06)	(1.15e-06)	(3.70e-06)	(1.10e-06)	(3.37e-06)	(1.10e-06)	(3.44e-06)	(1.05e-06)	(3.12e-06)	(1.23e-06)	(3.42e-06)	(1.34e-06)	(3.82e-06)
$\ln(GDPpc)$	-0.0664	-0.647***	-0.142**	-0.736***	-0.0685	-0.555**	-0.115	-0.674***	-0.130*	-0.731***	-0.0747	-0.611***	-0.0147	-0.652**
	(0.0777)	(0.227)	(0.0663)	(0.183)	(0.0830)	(0.224)	(0.0687)	(0.190)	(0.0680)	(0.176)	(0.0640)	(0.213)	(0.0840)	(0.265)
$\ln(GDPpc)^2$	-0.0131	0.0623	-0.000195	0.0733**	-0.00636	0.0589	-0.00637	0.0589	-0.00534	0.0641*	-0.0112	0.0571	-0.0169	0.0723
	(0.0146)	(0.0440)	(0.0123)	(0.0332)	(0.0143)	(0.0382)	(0.0128)	(0.0345)	(0.0127)	(0.0321)	(0.0125)	(0.0417)	(0.0159)	(0.0519)
Skilled	-0.00129	-0.00213											0.000875	0.00543**
	(0.000771)	(0.00226)											(0.000959)	(0.00262)
Semi-Skilled	-0.00120	-0.000287											-0.00126	0.00147
	(0.000966)	(0.00312)											(0.000932)	(0.00366)
Share “White”			0.00144***	0.00340**									0.00198***	0.00521***
			(0.000470)	(0.00140)									(0.000674)	(0.00171)
Informality					0.00160*	0.00405*							0.00203*	0.00602**
					(0.000845)	(0.00229)							(0.00103)	(0.00245)
Share Agric							0.185	0.472					-0.0630	-0.439
							(0.198)	(0.682)					(0.215)	(0.727)
Urbanization									-0.000603*	-0.00231**			-0.000744	-0.00350**
									(0.000300)	(0.00105)			(0.000468)	(0.00147)
Share Imports											-0.0543**	-0.142	-0.0348	-0.0622
											(0.0262)	(0.0907)	(0.0240)	(0.0841)
Share Exports											-0.0274	-0.0723	-0.0302*	-0.0667
											(0.0176)	(0.0622)	(0.0175)	(0.0603)
Constant	0.864***	1.904***	0.853***	1.870***	0.673***	1.407***	0.878***	1.927***	0.947***	2.176***	0.819***	1.807***	0.563***	1.300***
	(0.0984)	(0.271)	(0.0933)	(0.258)	(0.158)	(0.422)	(0.0951)	(0.272)	(0.0957)	(0.255)	(0.0851)	(0.276)	(0.155)	(0.432)
Observations	243	243	243	243	243	243	243	243	243	243	216	216	216	216
R^2	0.471	0.330	0.475	0.337	0.488	0.346	0.463	0.329	0.470	0.342	0.374	0.244	0.452	0.298
Adjusted R^2	0.457	0.313	0.464	0.323	0.477	0.332	0.451	0.315	0.458	0.328	0.357	0.223	0.419	0.256
Number of code	27	27	27	27	27	27	27	27	27	27	27	27	27	27

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Rural and Urban States, Pooled OLS

	Rural				Urban			
	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI	-0.00328	-0.00558	-0.00172	-0.00719	0.00239***	0.00582***	0.00138**	0.00387***
	(0.00286)	(0.00817)	(0.00283)	(0.00949)	(0.000556)	(0.00103)	(0.000578)	(0.00124)
ECI^2	-0.000149	-0.000257	-0.000145	-0.000371	-1.74e-05***	-4.30e-05***	-1.00e-05**	-2.79e-05***
	(9.75e-05)	(0.000284)	(0.000139)	(0.000502)	(3.84e-06)	(7.08e-06)	(3.75e-06)	(8.07e-06)
$\ln(GDPpc)$	0.221	0.158	0.258	0.542	-0.387***	-1.016***	-0.274***	-0.884***
	(0.153)	(0.441)	(0.306)	(0.895)	(0.0484)	(0.0874)	(0.0672)	(0.152)
$\ln(GDPpc)^2$	-0.0658	-0.0774	-0.0768	-0.202	0.0746***	0.187***	0.0570***	0.163***
	(0.0373)	(0.106)	(0.0740)	(0.220)	(0.00850)	(0.0152)	(0.0108)	(0.0237)
$\ln(Population)$	-0.0192	-0.0318			0.00143	0.0155**		
	(0.0117)	(0.0303)			(0.00254)	(0.00549)		
Schooling	-0.0116	-0.0477			-0.0273***	-0.0662***		
	(0.0106)	(0.0387)			(0.00479)	(0.00984)		
Skilled			0.00142	0.00565			-0.00522***	-0.0131***
			(0.00262)	(0.00814)			(0.00104)	(0.00270)
Semi-Skilled			-0.00411**	-0.00908**			-0.00282**	-0.00673*
			(0.00121)	(0.00360)			(0.00122)	(0.00328)
Share "White"			-0.000898	0.00173			8.13e-05	0.000396
			(0.000901)	(0.00283)			(0.000356)	(0.000855)
Informality			-0.000493	-0.00130			0.000488	-0.000622
			(0.00101)	(0.00261)			(0.000747)	(0.00211)
Share Agric			-0.0403	0.383			0.115	0.330
			(0.311)	(0.844)			(0.0802)	(0.213)
Urbanization			-1.10e-05	-0.00215			0.000799	0.00168
			(0.000655)	(0.00187)			(0.000961)	(0.00243)
Share Imports			-0.418*	-1.166*			-0.0582	-0.0978
			(0.187)	(0.611)			(0.0540)	(0.149)
Share Exports			-0.0782	-0.327			-0.0218	0.00408
			(0.112)	(0.396)			(0.0469)	(0.104)
Constant	0.738**	1.414*	0.515	0.729	1.199***	2.176***	0.980***	2.178***
	(0.273)	(0.664)	(0.402)	(1.148)	(0.0855)	(0.155)	(0.127)	(0.304)
Observations	72	72	64	64	171	171	152	152
R^2	0.433	0.409	0.599	0.530	0.684	0.690	0.733	0.688
Adjusted R^2	0.381	0.355	0.505	0.419	0.672	0.679	0.710	0.661

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Rural and Urban States, Fixed Effects

	Rural				Urban			
	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI	0.00503*	0.0184	0.00889**	0.0357*	0.000324	0.00103	-0.000112	2.47e-05
	(0.00255)	(0.0149)	(0.00305)	(0.0176)	(0.000432)	(0.00130)	(0.000362)	(0.00118)
ECI^2	0.000101	0.000388	0.000164	0.000830	-2.53e-06	-9.15e-06	-3.00e-06*	-8.80e-06*
	(8.21e-05)	(0.000456)	(8.97e-05)	(0.000527)	(1.78e-06)	(5.42e-06)	(1.51e-06)	(4.53e-06)
$\ln(GDPpc)$	-0.630**	-2.478***	-0.750***	-3.292***	-0.0452	-0.549**	0.00124	-0.474
	(0.197)	(0.696)	(0.183)	(0.928)	(0.114)	(0.217)	(0.135)	(0.416)
$\ln(GDPpc)^2$	0.106**	0.442**	0.131**	0.619**	-0.0114	0.0455	-0.0220	0.0232
	(0.0364)	(0.142)	(0.0424)	(0.238)	(0.0196)	(0.0398)	(0.0238)	(0.0760)
$\ln(Population)$	0.0625	0.429			-0.0139	0.0105		
	(0.110)	(0.428)			(0.0709)	(0.221)		
Schooling	0.0125	0.0395			-0.0127	-0.0262		
	(0.00944)	(0.0331)			(0.00734)	(0.0197)		
Skilled			0.00748***	0.0268**			0.000870	0.00422
			(0.00170)	(0.00770)			(0.00138)	(0.00374)
Semi-Skilled			0.00542*	0.0266**			-0.00250*	-0.00364
			(0.00242)	(0.0110)			(0.00125)	(0.00425)
Share "White"			-0.000887	-0.00132			0.00215**	0.00414**
			(0.00167)	(0.00640)			(0.000776)	(0.00192)
Informality			0.00198*	0.00682			0.00242*	0.00604*
			(0.000912)	(0.00398)			(0.00121)	(0.00300)
Share Agric			0.276	1.289			-0.0662	-0.955
			(0.391)	(1.176)			(0.260)	(0.690)
Urbanization			-0.00131*	-0.00572**			-0.000734	-0.00305
			(0.000561)	(0.00187)			(0.000981)	(0.00324)
Share Imports			-0.00116	0.156			-0.0303	-0.0949
			(0.0916)	(0.381)			(0.0255)	(0.0757)
Share Exports			-0.0570	-0.322			-0.0301	-0.0105
			(0.0650)	(0.283)			(0.0277)	(0.0846)
Constant	0.427	-2.664	1.275***	3.659***	1.052	1.771	0.572**	1.420**
	(1.567)	(6.308)	(0.195)	(0.640)	(1.002)	(3.316)	(0.209)	(0.570)
Observations	72	72	64	64	171	171	152	152
R^2	0.407	0.308	0.424	0.367	0.564	0.442	0.566	0.386
Adjusted R^2	0.353	0.244	0.289	0.218	0.548	0.421	0.528	0.333
Number of code	8	8	8	8	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Industry and Occupation Diversity, Pooled OLS

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI	0.00150**	0.00392***	0.00142**	0.00380***	0.00143**	0.00383***	0.00145**	0.00382***						
	(0.000633)	(0.00126)	(0.000632)	(0.00126)	(0.000633)	(0.00126)	(0.000630)	(0.00127)						
ECI^2	-1.11e-05**	-2.95e-05***	-1.12e-05**	-2.97e-05***	-1.11e-05**	-2.95e-05***	-1.12e-05**	-2.97e-05***						
	(4.44e-06)	(8.91e-06)	(4.45e-06)	(8.95e-06)	(4.49e-06)	(9.02e-06)	(4.39e-06)	(8.90e-06)						
$\ln(GDPpc)$	-0.261***	-0.733***	-0.257***	-0.733***	-0.253***	-0.722***	-0.264***	-0.737***	-0.288***	-0.816***	-0.284***	-0.807***	-0.296***	-0.821***
	(0.0645)	(0.150)	(0.0646)	(0.151)	(0.0640)	(0.149)	(0.0655)	(0.152)	(0.0624)	(0.148)	(0.0616)	(0.145)	(0.0637)	(0.149)
$\ln(GDPpc)^2$	0.0522***	0.138***	0.0508***	0.138***	0.0499***	0.135***	0.0526***	0.139***	0.0557***	0.151***	0.0549***	0.148***	0.0576***	0.152***
	(0.0114)	(0.0253)	(0.0113)	(0.0254)	(0.0112)	(0.0250)	(0.0116)	(0.0258)	(0.0106)	(0.0241)	(0.0104)	(0.0234)	(0.0108)	(0.0243)
$\ln(Population)$	-0.00210	0.00781	0.00719	0.0215*	0.00588	0.0179	0.00391	0.0194*	0.00126	0.00639	0.000443	0.00412	-0.00152	0.00459
	(0.00412)	(0.00923)	(0.00475)	(0.0113)	(0.00488)	(0.0118)	(0.00413)	(0.00966)	(0.00448)	(0.0107)	(0.00442)	(0.0108)	(0.00376)	(0.00878)
Schooling	-0.0201***	-0.0530***	-0.0161***	-0.0484***	-0.0157***	-0.0474***	-0.0186***	-0.0500***	-0.0137	-0.0416**	-0.0131	-0.0400*	-0.0159**	-0.0430**
	(0.00426)	(0.0103)	(0.00506)	(0.0121)	(0.00501)	(0.0119)	(0.00456)	(0.0111)	(0.00815)	(0.0200)	(0.00808)	(0.0197)	(0.00709)	(0.0180)
CNAE Diversity			-6.58e-05*	-4.16e-05	-9.44e-05***	-0.000119			-6.47e-05*	-4.18e-05	-9.30e-05***	-0.000120		
			(3.27e-05)	(9.55e-05)	(2.77e-05)	(7.42e-05)			(3.60e-05)	(0.000101)	(3.30e-05)	(7.93e-05)		
CBO Diversity			-8.97e-05*	-0.000244*			-0.000145***	-0.000278***	-8.14e-05*	-0.000226			-0.000141***	-0.000264**
			(4.63e-05)	(0.000128)			(4.12e-05)	(9.86e-05)	(4.71e-05)	(0.000133)			(4.72e-05)	(0.000106)
Constant	1.028***	1.795***	0.939***	1.712***	0.918***	1.655***	1.008***	1.756***	1.046***	1.989***	1.021***	1.922***	1.110***	2.031***
	(0.0883)	(0.183)	(0.0838)	(0.199)	(0.0823)	(0.191)	(0.0854)	(0.183)	(0.0886)	(0.226)	(0.0874)	(0.213)	(0.0895)	(0.200)
Observations	243	243	243	243	243	243	243	243	243	243	243	243	243	243
R^2	0.528	0.561	0.560	0.572	0.553	0.566	0.551	0.572	0.495	0.516	0.490	0.511	0.487	0.516
Adjusted R^2	0.516	0.550	0.545	0.557	0.540	0.553	0.537	0.559	0.483	0.504	0.479	0.501	0.476	0.506

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Industry and Occupation Diversity, Fixed Effects

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI	0.000249	0.000798	0.000243	0.000667	0.000240	0.000655	0.000247	0.000791						
	(0.000313)	(0.00101)	(0.000308)	(0.000986)	(0.000305)	(0.000963)	(0.000312)	(0.00101)						
ECI^2	-1.43e-06	-6.53e-06	-7.63e-07	-3.30e-06	-1.34e-06	-5.20e-06	-7.99e-07	-4.36e-06						
	(1.31e-06)	(4.22e-06)	(1.39e-06)	(4.76e-06)	(1.38e-06)	(4.51e-06)	(1.33e-06)	(4.50e-06)						
$\ln(GDPpc)$	-0.0879	-0.619***	-0.0721	-0.584**	-0.0894	-0.640***	-0.0714	-0.562**	-0.0764	-0.598**	-0.0948	-0.658***	-0.0755	-0.579**
	(0.0814)	(0.211)	(0.0847)	(0.227)	(0.0846)	(0.225)	(0.0810)	(0.212)	(0.0828)	(0.221)	(0.0821)	(0.217)	(0.0797)	(0.209)
$\ln(GDPpc)^2$	-0.00532	0.0575	-0.00745	0.0488	-0.00547	0.0553	-0.00740	0.0504	-0.00703	0.0504	-0.00481	0.0577*	-0.00693	0.0526
	(0.0140)	(0.0350)	(0.0136)	(0.0339)	(0.0137)	(0.0336)	(0.0138)	(0.0351)	(0.0134)	(0.0330)	(0.0134)	(0.0323)	(0.0136)	(0.0345)
$\ln(Population)$	-0.0359	0.0171	-0.00717	0.0899	-0.0379	-0.0110	-0.00618	0.119	-0.00855	0.0848	-0.0401	-0.0191	-0.00715	0.114
	(0.0448)	(0.163)	(0.0523)	(0.177)	(0.0459)	(0.170)	(0.0508)	(0.171)	(0.0515)	(0.173)	(0.0446)	(0.164)	(0.0499)	(0.167)
Schooling	-0.00605	-0.0161	-0.00591	-0.0202	-0.00646	-0.0220	-0.00574	-0.0150	-0.00557	-0.0192	-0.00609	-0.0209	-0.00529	-0.0135
	(0.00680)	(0.0227)	(0.00674)	(0.0224)	(0.00658)	(0.0218)	(0.00692)	(0.0233)	(0.00661)	(0.0221)	(0.00645)	(0.0215)	(0.00678)	(0.0230)
CNAE Diversity			3.34e-06	9.78e-05	7.84e-06	0.000113			4.89e-06	0.000103	9.63e-06	0.000118		
			(2.98e-05)	(0.000124)	(2.96e-05)	(0.000124)			(3.00e-05)	(0.000123)	(2.97e-05)	(0.000123)		
CBO Diversity			-7.49e-05**	-0.000246**			-7.53e-05**	-0.000258**	-7.52e-05**	-0.000248**			-7.58e-05**	-0.000261**
			(3.32e-05)	(9.86e-05)			(3.24e-05)	(9.99e-05)	(3.30e-05)	(9.78e-05)			(3.19e-05)	(9.84e-05)
Constant	1.392**	1.657	0.966	0.628	1.425**	2.136	0.950	0.142	0.992	0.719	1.464**	2.274	0.968	0.229
	(0.648)	(2.438)	(0.773)	(2.700)	(0.676)	(2.594)	(0.735)	(2.549)	(0.761)	(2.638)	(0.655)	(2.503)	(0.722)	(2.490)
Observations	243	243	243	243	243	243	243	243	243	243	243	243	243	243
R^2	0.469	0.330	0.477	0.342	0.469	0.334	0.476	0.340	0.476	0.342	0.468	0.333	0.476	0.339
Adjusted R^2	0.456	0.313	0.459	0.320	0.453	0.314	0.461	0.320	0.462	0.325	0.457	0.319	0.465	0.325
Number of code	27	27	27	27	27	27	27	27	27	27	27	27	27	27

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix I: Summary Statistics

Table 9: Descriptive Statistics

Variable		Mean	SD	Min	Max	Observations
Gini (IPEA)	Overall	0.537	0.040	0.421	0.634	N = 324
	Between		0.030	0.454	0.610	n = 27
	Within		0.027	0.470	0.612	T = 12
Gini (RAIS)	Overall	0.467	0.032	0.403	0.568	N = 324
	Between		0.029	0.422	0.559	n = 27
	Within		0.014	0.431	0.518	T = 12
Theil	Overall	0.599	0.116	0.331	1.313	N = 324
	Between		0.080	0.401	0.733	n = 27
	Within		0.085	0.389	1.179	T = 12
ECI	Overall	0.452	28.65	-29.26	153.6	N = 351
	Between		29.00	-19.96	141.9	n = 27
	Within		2.953	-16.97	12.18	T = 13
ln(GDPpc)	Overall	2.567	0.505	1.600	4.076	N = 270
	Between		0.503	1.795	3.971	n = 27
	Within		0.101	2.321	2.857	T = 10
Share “White”	Overall	39.99	18.58	16.96	89.35	N = 243
	Between		18.79	21.33	87.57	n = 27
	Within		2.005	34.33	46.80	T = 9
Informality	Overall	56.21	11.88	32.20	84.92	N = 324
	Between		11.19	37.13	75.43	n = 27
	Within		4.482	45.91	73.61	T = 12
ln(Population)	Overall	15.23	1.064	12.76	17.60	N = 351
	Between		1.081	12.94	17.53	n = 27
	Within		0.061	15.04	15.41	T = 13
Schooling	Overall	6.582	1.195	3.982	10.08	N = 324
	Between		1.055	4.861	9.370	n = 27
	Within		0.593	5.017	8.085	T = 12

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Variable		Mean	SD	Min	Max	Observations
Unskilled	Overall	14.11	5.984	3.990	31.88	N = 243
	Between		5.654	5.118	27.17	n = 27
	Within		2.213	7.667	20.33	T = 9
Semi-Skilled	Overall	26.07	4.177	17.47	37.92	N = 243
	Between		3.671	21.06	34.69	n = 27
	Within		2.101	18.88	31.09	T = 9
Skilled	Overall	21.18	6.019	8.070	41.03	N = 243
	Between		5.255	11.86	35.62	n = 27
	Within		3.086	13.58	30.55	T = 9
Share Agric	Overall	0.0396	0.0306	0.0048	0.146	N = 351
	Between		0.0304	0.0059	0.133	n = 27
	Within		0.0066	0.0220	0.0694	T = 13
Urbanization	Overall	52.18	7.084	36.23	71.38	N = 243
	Between		6.218	38.77	63.88	n = 27
	Within		3.576	44.11	69.18	T = 9
Technology	Overall	6.024e+07	1.384e+08	15998.4	8.865e+08	N = 237
	Between		1.30e+08	424166.8	6.74e+08	n = 27
	Within		4.86e+07	-3.31e+08	2.73e+08	T = 8.78
Share Imports	Overall	0.0313	0.0482	5.32e-05	0.362	N = 243
	Between		0.0344	0.00033	0.158	n = 27
	Within		0.0343	-0.0565	0.235	T = 9
Share Exports	Overall	0.0413	0.0557	0.000150	0.415	N = 243
	Between		0.0373	0.00084	0.133	n = 27
	Within		0.0419	-0.0393	0.323	T = 9
Industry Diversity	Overall	500.85	110.72	207	667	N = 324
	Between		89.35	283.25	614.17	n = 27
	Within		67.44	390.10	568.60	T = 12
Occupation Diversity	Overall	543.91	55.15	293	598	N = 324
	Between		44.45	405	580.33	n = 27
	Within		33.66	425.49	592.74	T = 12

Appendix II: Informality Measures

Table 10: Different Informality Measures, Pooled OLS and Fixed Effects

	Dependent Variable: Gini							
	Pooled OLS				Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI	0.00150**	0.00151**	0.00154**	0.00149**	0.000249	0.000227	0.000249	0.000208
	(0.000633)	(0.000551)	(0.000586)	(0.000540)	(0.000313)	(0.000294)	(0.000307)	(0.000289)
ECI^2	-1.11e-05**	-1.11e-05***	-1.12e-05**	-1.09e-05***	-1.43e-06	-1.83e-06	-1.86e-06	-1.90e-06
	(4.44e-06)	(3.86e-06)	(4.10e-06)	(3.80e-06)	(1.31e-06)	(1.22e-06)	(1.31e-06)	(1.24e-06)
$\ln(GDPpc)$	-0.261***	-0.214***	-0.214***	-0.209***	-0.0879	-0.0633	-0.0604	-0.0674
	(0.0645)	(0.0669)	(0.0663)	(0.0667)	(0.0814)	(0.0826)	(0.0852)	(0.0851)
$\ln(GDPpc)^2$	0.0522***	0.0469***	0.0467***	0.0464***	-0.00532	-0.00542	-0.00700	-0.00665
	(0.0114)	(0.0111)	(0.0112)	(0.0110)	(0.0140)	(0.0137)	(0.0140)	(0.0140)
$\ln(Population)$	-0.00210	0.000160	-0.000235	0.000132	-0.0359	0.00781	0.0109	0.00960
	(0.00412)	(0.00528)	(0.00523)	(0.00522)	(0.0448)	(0.0364)	(0.0358)	(0.0373)
Schooling	-0.0201***	-0.0189***	-0.0179***	-0.0194***	-0.00605	-0.000405	0.00104	-0.000383
	(0.00426)	(0.00366)	(0.00394)	(0.00369)	(0.00680)	(0.00667)	(0.00664)	(0.00658)
Informal(1)		0.00109				0.00178*		
		(0.000779)				(0.000909)		
Informal(2)			0.00109				0.00178**	
			(0.000786)				(0.000809)	
Informal(3)				0.00117				0.00164*
				(0.000786)				(0.000883)
Constant	1.028***	0.834***	0.836***	0.826***	1.392**	0.521	0.470	0.526
	(0.0883)	(0.172)	(0.176)	(0.169)	(0.648)	(0.519)	(0.519)	(0.543)
Observations	243	243	243	243	243	243	243	243
R^2	0.528	0.549	0.547	0.551	0.469	0.490	0.492	0.488
Adjusted R^2	0.516	0.536	0.533	0.538	0.456	0.475	0.477	0.473
Number of code					27	27	27	27

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix III: Results Excluding Outliers

Table 11: Baseline Model, Pooled OLS, Excluding Outliers

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ECI	0.000693	0.000545	0.000689	0.000613	0.00153	0.00291	0.00178*	0.00408**			0.00238***	0.00587***
	(0.000727)	(0.00186)	(0.000876)	(0.00193)	(0.000949)	(0.00204)	(0.00102)	(0.00192)			(0.000635)	(0.00134)
ECI^2	-5.21e-05	-0.000180*	-4.26e-05	-0.000134*	-1.51e-05	-5.89e-05	-1.60e-05	-6.28e-05			3.23e-05	4.58e-05
	(3.31e-05)	(9.05e-05)	(3.42e-05)	(7.20e-05)	(3.68e-05)	(8.13e-05)	(3.68e-05)	(6.94e-05)			(2.44e-05)	(6.00e-05)
$\ln(GDPpc)$			-0.0752	-0.547*	0.0290	-0.261	0.0667	-0.0850	-0.0223	-0.301		
			(0.102)	(0.271)	(0.109)	(0.272)	(0.0907)	(0.213)	(0.137)	(0.319)		
$\ln(GDPpc)^2$			0.00441	0.0760	-0.00772	0.0427	-0.0164	0.00243	-6.65e-05	0.0419		
			(0.0212)	(0.0548)	(0.0214)	(0.0528)	(0.0174)	(0.0396)	(0.0283)	(0.0656)		
Schooling					-0.0215***	-0.0589***	-0.0200***	-0.0519***	-0.0156*	-0.0418**	-0.0266***	-0.0795***
					(0.00508)	(0.0147)	(0.00491)	(0.0122)	(0.00831)	(0.0201)	(0.00274)	(0.00545)
$\ln(Population)$							0.00451	0.0210**	-0.00181	0.00517	0.000578	0.0136*
							(0.00418)	(0.00899)	(0.00420)	(0.00975)	(0.00378)	(0.00791)
Constant	0.542***	0.614***	0.709***	1.504***	0.662***	1.375***	0.547***	0.840***	0.723***	1.276***	0.707***	0.928***
	(0.00461)	(0.0158)	(0.122)	(0.329)	(0.118)	(0.300)	(0.109)	(0.248)	(0.155)	(0.382)	(0.0584)	(0.122)
Observations	300	300	225	225	225	225	225	225	225	225	300	300
R^2	0.086	0.054	0.494	0.513	0.561	0.568	0.572	0.593	0.459	0.515	0.576	0.531
Adjusted R^2	0.0796	0.0473	0.484	0.504	0.551	0.559	0.560	0.582	0.449	0.507	0.570	0.525

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Extended Model, Pooled OLS, Excluding Outliers

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI	0.000374	-0.000208	0.00107	0.00183	0.000522	0.000507	0.000982	0.00185	0.000678	0.000440	0.000301	-0.000601	2.78e-05	-0.000372
	(0.000786)	(0.00154)	(0.000938)	(0.00218)	(0.000901)	(0.00196)	(0.000933)	(0.00213)	(0.000893)	(0.00202)	(0.000893)	(0.00230)	(0.000885)	(0.00210)
ECI^2	-6.19e-05*	-0.000186***	-3.04e-05	-9.48e-05	-4.90e-05	-0.000138*	-2.86e-05	-7.52e-05	-4.35e-05	-0.000150*	-6.91e-05**	-0.000214***	-7.97e-05**	-0.000208***
	(3.24e-05)	(6.18e-05)	(3.67e-05)	(8.24e-05)	(3.45e-05)	(7.06e-05)	(3.78e-05)	(8.56e-05)	(3.47e-05)	(7.71e-05)	(2.92e-05)	(7.35e-05)	(3.38e-05)	(7.26e-05)
$\ln(GDPpc)$	0.0398	-0.236	-0.0354	-0.418	-0.0744	-0.546*	-0.0884	-0.602**	-0.0724	-0.501*	-0.124	-0.673**	0.0513	-0.197
	(0.0816)	(0.194)	(0.0992)	(0.246)	(0.105)	(0.273)	(0.105)	(0.285)	(0.101)	(0.257)	(0.108)	(0.285)	(0.0975)	(0.250)
$\ln(GDPpc)^2$	-0.00662	0.0462	-0.00515	0.0451	0.00679	0.0775	0.00680	0.0860	0.00401	0.0693	0.0160	0.105*	-0.00649	0.0379
	(0.0166)	(0.0390)	(0.0208)	(0.0504)	(0.0219)	(0.0553)	(0.0215)	(0.0569)	(0.0209)	(0.0529)	(0.0225)	(0.0583)	(0.0196)	(0.0487)
Skilled	-0.00478***	-0.0129***											-0.00452***	-0.0114***
	(0.000922)	(0.00230)											(0.00100)	(0.00266)
Semi-Skilled	-0.00225***	-0.00601***											-0.00385***	-0.00959***
	(0.000680)	(0.00162)											(0.000851)	(0.00236)
Share "White"			0.000244	0.000785									0.000354	0.00103
			(0.000234)	(0.000651)									(0.000306)	(0.000763)
Informality					0.000533	0.000338							0.000626	0.000691
					(0.000564)	(0.00150)							(0.000608)	(0.00148)
Share Agric							0.0842	0.355					0.0508	0.269
							(0.0883)	(0.250)					(0.0725)	(0.181)
Urbanization									-7.47e-05	-0.00123			0.000318	-6.04e-05
									(0.000360)	(0.000971)			(0.000348)	(0.000967)
Share Imports											-0.0855	-0.124	-0.0522	-0.0464
											(0.0639)	(0.179)	(0.0574)	(0.147)
Share Exports											-0.0486	-0.120	-0.0316	-0.0897
											(0.0430)	(0.115)	(0.0301)	(0.0783)
Constant	0.649***	1.342***	0.662***	1.353***	0.660***	1.473***	0.723***	1.565***	0.708***	1.495***	0.763***	1.646***	0.592***	1.283***
	(0.0971)	(0.232)	(0.118)	(0.298)	(0.131)	(0.367)	(0.126)	(0.349)	(0.121)	(0.323)	(0.125)	(0.341)	(0.128)	(0.320)
Observations	225	225	225	225	225	225	225	225	225	225	200	200	200	200
R^2	0.596	0.595	0.499	0.519	0.499	0.513	0.498	0.521	0.494	0.516	0.521	0.531	0.641	0.621
Adjusted R^2	0.585	0.584	0.488	0.508	0.488	0.502	0.487	0.510	0.482	0.505	0.506	0.516	0.617	0.597

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Baseline Model, Fixed Effects, Excluding Outliers

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ECI	-0.000393	-0.00116	-0.000158	9.74e-05	-0.000141	0.000127	-0.000101	0.000133			0.000382	0.000760
	(0.000950)	(0.00212)	(0.000697)	(0.00221)	(0.000724)	(0.00222)	(0.000666)	(0.00226)			(0.000442)	(0.00188)
ECI^2	-4.33e-05	-0.000136*	-1.46e-05	-2.58e-05	-1.93e-05	-3.40e-05	-1.63e-05	-3.35e-05			1.73e-06	-2.99e-05
	(3.42e-05)	(7.49e-05)	(2.11e-05)	(6.72e-05)	(2.36e-05)	(7.32e-05)	(2.28e-05)	(7.66e-05)			(1.61e-05)	(6.48e-05)
$\ln(GDPpc)$			-0.122	-0.762***	-0.0840	-0.695***	-0.0776	-0.694***	-0.0854	-0.716***		
			(0.0753)	(0.205)	(0.0882)	(0.242)	(0.0928)	(0.243)	(0.0902)	(0.237)		
$\ln(GDPpc)^2$			-0.00539	0.0766*	-0.00620	0.0751*	-0.00581	0.0752*	-0.00477	0.0781*		
			(0.0145)	(0.0384)	(0.0150)	(0.0397)	(0.0158)	(0.0399)	(0.0155)	(0.0396)		
Schooling					-0.00857	-0.0150	-0.00599	-0.0147	-0.00525	-0.0126	-0.0298***	-0.0802***
					(0.00690)	(0.0210)	(0.00685)	(0.0233)	(0.00661)	(0.0226)	(0.00665)	(0.0195)
$\ln(Population)$							-0.0551	-0.00758	-0.0577	-0.0143	-0.0370	0.0147
							(0.0458)	(0.176)	(0.0443)	(0.171)	(0.0584)	(0.171)
Constant	0.536***	0.601***	0.880***	2.021***	0.844***	1.958***	1.643**	2.068	1.690**	2.190	1.288	0.895
	(0.00412)	(0.00957)	(0.0988)	(0.275)	(0.110)	(0.305)	(0.659)	(2.605)	(0.635)	(2.516)	(0.849)	(2.483)
Observations	300	300	225	225	225	225	225	225	225	225	300	300
R^2	0.008	0.008	0.446	0.321	0.454	0.323	0.459	0.323	0.457	0.322	0.520	0.299
Adjusted R^2	0.00139	0.00146	0.436	0.309	0.441	0.308	0.444	0.305	0.447	0.310	0.514	0.289
Number of code	25	25	25	25	25	25	25	25	25	25	25	25

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Extended Model, Fixed Effects, Excluding Outliers

	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI	-0.000226	0.000127	0.000258	0.00108	-0.000346	-0.000385	-0.000162	8.71e-05	-0.000303	-0.000447	-0.000270	0.000188	-0.000435	-0.000399
	(0.000695)	(0.00222)	(0.000650)	(0.00214)	(0.000673)	(0.00217)	(0.000698)	(0.00221)	(0.000768)	(0.00245)	(0.000861)	(0.00291)	(0.000638)	(0.00268)
ECI^2	-1.82e-05	-3.33e-05	-1.87e-06	4.31e-06	-2.48e-05	-5.18e-05	-1.65e-05	-3.10e-05	-2.21e-05	-5.40e-05	-2.92e-05	-5.60e-05	-3.55e-05*	-8.34e-05
	(2.31e-05)	(7.36e-05)	(2.15e-05)	(7.03e-05)	(2.12e-05)	(6.73e-05)	(2.20e-05)	(6.89e-05)	(2.36e-05)	(7.47e-05)	(2.37e-05)	(8.12e-05)	(1.77e-05)	(7.32e-05)
$\ln(GDPpc)$	-0.0621	-0.738***	-0.143*	-0.810***	-0.0776	-0.647**	-0.125	-0.770***	-0.135*	-0.812***	-0.101	-0.800***	-0.0333	-0.863***
	(0.0884)	(0.261)	(0.0755)	(0.207)	(0.0927)	(0.246)	(0.0753)	(0.205)	(0.0735)	(0.190)	(0.0609)	(0.191)	(0.0953)	(0.284)
$\ln(GDPpc)^2$	-0.0133	0.0819	0.000195	0.0897**	-0.00353	0.0813*	-0.00391	0.0807**	-0.00377	0.0827**	-0.00497	0.101**	-0.0123	0.117**
	(0.0165)	(0.0510)	(0.0144)	(0.0390)	(0.0165)	(0.0438)	(0.0144)	(0.0388)	(0.0140)	(0.0355)	(0.0122)	(0.0376)	(0.0182)	(0.0556)
Skilled	-0.00135	-0.00178											0.000995	0.00697**
	(0.000828)	(0.00245)											(0.00106)	(0.00266)
Semi-Skilled	-0.00116	0.000115											-0.00115	0.00201
	(0.00100)	(0.00327)											(0.000936)	(0.00374)
Share "White"			0.00135**	0.00319**									0.00186**	0.00482***
			(0.000491)	(0.00147)									(0.000678)	(0.00170)
Informality					0.00167*	0.00428*							0.00216**	0.00672**
					(0.000864)	(0.00233)							(0.00104)	(0.00240)
Share Agric							0.181	0.504					-0.0511	-0.338
							(0.200)	(0.689)					(0.214)	(0.727)
Urbanization									-0.000607**	-0.00228**			-0.000784*	-0.00368**
									(0.000290)	(0.00104)			(0.000457)	(0.00146)
Share Imports											-0.0538**	-0.150	-0.0350	-0.0734
											(0.0255)	(0.0901)	(0.0237)	(0.0834)
Share Exports											-0.0288*	-0.0899	-0.0296*	-0.0910
											(0.0166)	(0.0615)	(0.0165)	(0.0570)
Constant	0.838***	1.963***	0.844***	1.937***	0.659***	1.455***	0.870***	1.995***	0.933***	2.223***	0.828***	1.976***	0.559***	1.452***
	(0.109)	(0.302)	(0.104)	(0.279)	(0.167)	(0.443)	(0.102)	(0.285)	(0.102)	(0.268)	(0.0804)	(0.252)	(0.161)	(0.441)
Observations	225	225	225	225	225	225	225	225	225	225	200	200	200	200
R^2	0.457	0.322	0.459	0.328	0.477	0.342	0.448	0.323	0.456	0.335	0.357	0.238	0.437	0.294
Adjusted R^2	0.442	0.304	0.447	0.313	0.465	0.326	0.436	0.307	0.443	0.320	0.337	0.214	0.401	0.249
Number of code	25	25	25	25	25	25	25	25	25	25	25	25	25	25

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Rural and Urban States, Pooled OLS, Excluding Outliers

	Rural				Urban			
	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI	-0.00328	-0.00558	-0.00172	-0.00719	0.00213*	0.00494**	0.000217	0.00117
	(0.00286)	(0.00817)	(0.00283)	(0.00949)	(0.00104)	(0.00191)	(0.000835)	(0.00188)
ECI^2	-0.000149	-0.000257	-0.000145	-0.000371	-2.42e-05	-8.28e-05	-7.87e-05**	-0.000185**
	(9.75e-05)	(0.000284)	(0.000139)	(0.000502)	(3.91e-05)	(7.88e-05)	(3.16e-05)	(6.70e-05)
$\ln(GDPpc)$	0.221	0.158	0.258	0.542	-0.0643	-0.405*	0.0273	-0.363
	(0.153)	(0.441)	(0.306)	(0.895)	(0.120)	(0.213)	(0.150)	(0.343)
$\ln(GDPpc)^2$	-0.0658	-0.0774	-0.0768	-0.202	0.00913	0.0630	-0.00137	0.0636
	(0.0373)	(0.106)	(0.0740)	(0.220)	(0.0235)	(0.0414)	(0.0294)	(0.0665)
$\ln(Population)$	-0.0192	-0.0318			0.00620*	0.0248***		
	(0.0117)	(0.0303)			(0.00323)	(0.00664)		
Schooling	-0.0116	-0.0477			-0.0242***	-0.0596***		
	(0.0106)	(0.0387)			(0.00487)	(0.0108)		
Skilled			0.00142	0.00565			-0.00576***	-0.0141***
			(0.00262)	(0.00814)			(0.00111)	(0.00283)
Semi Skilled			-0.00411**	-0.00908**			-0.00342**	-0.00778**
			(0.00121)	(0.00360)			(0.00117)	(0.00339)
Share “White”			-0.000898	0.00173			0.000347	0.000817
			(0.000901)	(0.00283)			(0.000354)	(0.000877)
Informality			-0.000493	-0.00130			0.000544	-0.000500
			(0.00101)	(0.00261)			(0.000726)	(0.00206)
Share Agric			-0.0403	0.383			0.0175	0.140
			(0.311)	(0.844)			(0.0871)	(0.219)
Urbanization			-1.10e-05	-0.00215			0.000410	0.000951
			(0.000655)	(0.00187)			(0.000826)	(0.00214)
Share Imports			-0.418*	-1.166*			-0.0288	-0.0308
			(0.187)	(0.611)			(0.0590)	(0.158)
Share Exports			-0.0782	-0.327			0.00490	0.0350
			(0.112)	(0.396)			(0.0386)	(0.0863)
Constant	0.738**	1.414*	0.515	0.729	0.718***	1.257***	0.634***	1.577***
	(0.273)	(0.664)	(0.402)	(1.148)	(0.152)	(0.267)	(0.201)	(0.448)
Observations	72	72	64	64	153	153	136	136
R^2	0.433	0.409	0.599	0.530	0.672	0.700	0.700	0.678
Adjusted R^2	0.381	0.355	0.505	0.419	0.658	0.688	0.670	0.646

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Rural and Urban States, Fixed Effects, Excluding Outliers

	Rural				Urban			
	Gini	Theil	Gini	Theil	Gini	Theil	Gini	Theil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI	0.00503*	0.0184	0.00889**	0.0357*	-0.000205	-0.000297	-0.000824	-0.00208
	(0.00255)	(0.0149)	(0.00305)	(0.0176)	(0.000823)	(0.00230)	(0.000632)	(0.00234)
ECI^2	0.000101	0.000388	0.000164	0.000830	-2.80e-05	-6.89e-05	-3.17e-05	-8.15e-05
	(8.21e-05)	(0.000456)	(8.97e-05)	(0.000527)	(2.82e-05)	(7.54e-05)	(2.31e-05)	(7.71e-05)
$\ln(GDPpc)$	-0.630**	-2.478***	-0.750***	-3.292***	0.0230	-0.561*	-0.0524	-0.896
	(0.197)	(0.696)	(0.183)	(0.928)	(0.120)	(0.266)	(0.206)	(0.642)
$\ln(GDPpc)^2$	0.106**	0.442**	0.131**	0.619**	-0.0215	0.0523	-0.0110	0.105
	(0.0364)	(0.142)	(0.0424)	(0.238)	(0.0201)	(0.0452)	(0.0375)	(0.119)
$\ln(Population)$	0.0625	0.429			-0.0501	-0.0518		
	(0.110)	(0.428)			(0.0733)	(0.240)		
Schooling	0.0125	0.0395			-0.0130	-0.0247		
	(0.00944)	(0.0331)			(0.00757)	(0.0211)		
Skilled			0.00748***	0.0268**			0.00119	0.00670
			(0.00170)	(0.00770)			(0.00171)	(0.00409)
Semi Skilled			0.00542*	0.0266**			-0.00232*	-0.00300
			(0.00242)	(0.0110)			(0.00127)	(0.00430)
Share "White"			-0.000887	-0.00132			0.00209**	0.00414*
			(0.00167)	(0.00640)			(0.000873)	(0.00217)
Informality			0.00198*	0.00682			0.00262*	0.00707**
			(0.000912)	(0.00398)			(0.00129)	(0.00304)
Share Agric			0.276	1.289			-0.0555	-0.880
			(0.391)	(1.176)			(0.257)	(0.665)
Urbanization			-0.00131*	-0.00572**			-0.000874	-0.00351
			(0.000561)	(0.00187)			(0.000974)	(0.00322)
Share Imports			-0.00116	0.156			-0.0312	-0.111
			(0.0916)	(0.381)			(0.0260)	(0.0841)
Share Exports			-0.0570	-0.322			-0.0349	-0.0599
			(0.0650)	(0.283)			(0.0300)	(0.0885)
Constant	0.427	-2.664	1.275***	3.659***	1.475	2.650	0.598**	1.793**
	(1.567)	(6.308)	(0.195)	(0.640)	(1.043)	(3.540)	(0.254)	(0.765)
Observations	72	72	64	64	153	153	136	136
R^2	0.407	0.308	0.424	0.367	0.558	0.434	0.552	0.382
Adjusted R^2	0.353	0.244	0.289	0.218	0.540	0.411	0.508	0.322
Number of code	8	8	8	8	17	17	17	17

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix IV: Alternative Gini Dataset

Table 17: Baseline Model, Pooled OLS, Using Gini (RAIS)

	Dependent Variable: Gini (RAIS)					
	(1)	(2)	(3)	(4)	(5)	(6)
ECI	0.00148**	0.00121**	0.00114**	0.000982		0.00126**
	(0.000574)	(0.000559)	(0.000535)	(0.000650)		(0.000597)
ECI^2	-1.03e-05**	-8.91e-06**	-8.39e-06**	-6.96e-06		-8.77e-06*
	(4.22e-06)	(3.98e-06)	(3.77e-06)	(4.91e-06)		(4.67e-06)
$\ln(GDPpc)$		-0.161**	-0.179***	-0.178***	-0.201***	
		(0.0604)	(0.0610)	(0.0594)	(0.0554)	
$\ln(GDPpc)^2$		0.0324***	0.0328***	0.0332***	0.0367***	
		(0.0109)	(0.0103)	(0.00970)	(0.00855)	
$\ln(Population)$				-0.00307	-0.00564	-0.00269
				(0.00548)	(0.00408)	(0.00461)
Schooling			0.00834	0.00701	0.00953	0.00483
			(0.00573)	(0.00659)	(0.00744)	(0.00637)
Constant	0.475***	0.668***	0.661***	0.708***	0.760***	0.484***
	(0.00708)	(0.0819)	(0.0770)	(0.111)	(0.0875)	(0.0771)
Observations	324	270	243	243	243	297
R^2	0.128	0.333	0.349	0.356	0.313	0.167
Adjusted R^2	0.123	0.323	0.335	0.340	0.301	0.156

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Extended Model, Pooled OLS, Using Gini (RAIS)

	Dependent Variable: Gini (RAIS)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ECI	0.00103*	0.000802	0.00107**	0.000991*	0.00120**	0.000976	0.000182
	(0.000502)	(0.000513)	(0.000486)	(0.000557)	(0.000561)	(0.000708)	(0.000417)
ECI^2	-7.69e-06**	-5.57e-06	-7.43e-06**	-7.51e-06*	-8.97e-06**	-7.35e-06	-1.50e-06
	(3.51e-06)	(3.76e-06)	(3.50e-06)	(3.86e-06)	(3.98e-06)	(4.97e-06)	(2.91e-06)
$\ln(GDPpc)$	-0.0730	-0.121**	-0.0719	-0.117*	-0.183***	-0.123**	0.0367
	(0.0633)	(0.0488)	(0.0609)	(0.0591)	(0.0572)	(0.0513)	(0.0506)
$\ln(GDPpc)^2$	0.0204*	0.0278***	0.0228**	0.0244**	0.0345***	0.0266***	0.00498
	(0.0102)	(0.00793)	(0.00956)	(0.0107)	(0.0101)	(0.00886)	(0.00755)
Skilled	-0.00161						-0.00304***
	(0.00153)						(0.00106)
Semi-Skilled	-0.00224**						-0.00234**
	(0.00103)						(0.00108)
Share “White”		-0.000677***					-0.000557**
		(0.000226)					(0.000224)
Informality			0.00182***				0.000504
			(0.000643)				(0.000420)
Share Agric				-0.303***			-0.335**
				(0.108)			(0.122)
Urbanization					0.00123**		0.00149***
					(0.000494)		(0.000535)
Share Imports						-0.0819	-0.0439
						(0.0700)	(0.0589)
Share Exports						-0.132*	-0.0877**
						(0.0686)	(0.0415)
Constant	0.618***	0.623***	0.400***	0.621***	0.648***	0.618***	0.406***
	(0.0720)	(0.0664)	(0.120)	(0.0788)	(0.0779)	(0.0704)	(0.0686)
Observations	243	243	243	270	243	243	216
R^2	0.377	0.425	0.430	0.413	0.373	0.420	0.689
Adjusted R^2	0.361	0.413	0.418	0.402	0.360	0.405	0.670

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Baseline Model, Fixed Effects, Using Gini (RAIS)

	Dependent Variable: Gini (RAIS)					
	(1)	(2)	(3)	(4)	(5)	(6)
ECI	0.000175	-0.000273	-0.000204	-0.000208		0.000140
	(0.000529)	(0.000217)	(0.000198)	(0.000192)		(0.000235)
ECI^2	1.78e-06	1.32e-06	6.90e-07	9.97e-07		-6.01e-07
	(1.95e-06)	(1.02e-06)	(9.99e-07)	(9.53e-07)		(8.81e-07)
$\ln(GDPpc)$		-0.240***	-0.248***	-0.249***	-0.244***	
		(0.0694)	(0.0711)	(0.0719)	(0.0712)	
$\ln(GDPpc)^2$		0.0318**	0.0344**	0.0349**	0.0343**	
		(0.0129)	(0.0127)	(0.0128)	(0.0126)	
$\ln(Population)$				-0.0168	-0.0154	-0.0338
				(0.0246)	(0.0244)	(0.0378)
Schooling			-0.00107	-0.000210	-0.000603	-0.0148***
			(0.00322)	(0.00337)	(0.00345)	(0.00363)
Constant	0.465***	0.869***	0.879***	1.125***	1.101***	1.079*
	(0.00137)	(0.0921)	(0.0926)	(0.349)	(0.343)	(0.559)
Observations	324	270	243	243	243	297
R^2	0.005	0.526	0.508	0.509	0.508	0.496
Adjusted R^2	-0.00146	0.519	0.498	0.497	0.499	0.489
Number of code	27	27	27	27	27	27

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Extended Model, Fixed Effects, Using Gini (RAIS)

	Dependent Variable: Gini (RAIS)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ECI	-0.000176	-0.000157	-0.000213	-0.000232	-0.000223	-0.000341*	-0.000322*
	(0.000189)	(0.000204)	(0.000209)	(0.000222)	(0.000206)	(0.000192)	(0.000176)
ECI^2	7.65e-07	5.78e-07	7.29e-07	1.00e-06	7.63e-07	1.95e-06*	1.23e-06
	(9.81e-07)	(9.85e-07)	(9.96e-07)	(1.09e-06)	(9.55e-07)	(9.79e-07)	(8.73e-07)
$\ln(GDPpc)$	-0.242***	-0.267***	-0.248***	-0.240***	-0.250***	-0.307***	-0.353***
	(0.0739)	(0.0663)	(0.0703)	(0.0674)	(0.0701)	(0.0633)	(0.0826)
$\ln(GDPpc)^2$	0.0350**	0.0383***	0.0343**	0.0331**	0.0339**	0.0471***	0.0584***
	(0.0134)	(0.0124)	(0.0126)	(0.0121)	(0.0129)	(0.0116)	(0.0153)
Skilled	-0.000573						-0.000615
	(0.000459)						(0.000644)
Semi-Skilled	-0.000172						-0.000632
	(0.000458)						(0.000578)
Share “White”		0.000815**					0.000636*
		(0.000352)					(0.000344)
Informality			0.000148				-0.000313
			(0.000247)				(0.000331)
Share Agric				0.266			0.223
				(0.184)			(0.165)
Urbanization					9.67e-05		0.000337
					(0.000243)		(0.000248)
Share Imports						-0.0389	-0.0172
						(0.0229)	(0.0256)
Share Exports						-0.0308**	-0.0430***
						(0.0116)	(0.0102)
Constant	0.869***	0.861***	0.862***	0.848***	0.873***	0.938***	0.974***
	(0.0963)	(0.0912)	(0.105)	(0.0963)	(0.0986)	(0.0858)	(0.120)
Observations	243	243	243	270	243	243	216
R^2	0.512	0.524	0.508	0.541	0.508	0.581	0.602
Adjusted R^2	0.500	0.514	0.498	0.532	0.498	0.570	0.578
Number of code	27	27	27	27	27	27	27

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: Rural and Urban States, Pooled OLS, Using Gini (RAIS)

	Dependent Variable: Gini (RAIS)			
	Rural		Urban	
	(1)	(2)	(3)	(4)
ECI	-0.00128	0.00161	0.00163**	0.000422
	(0.00284)	(0.00145)	(0.000613)	(0.000590)
ECI^2	-9.13e-05	-8.42e-06	-1.15e-05**	-3.26e-06
	(8.47e-05)	(5.19e-05)	(4.65e-06)	(4.20e-06)
$\ln(GDPpc)$	0.170	-0.161	-0.276***	0.0243
	(0.335)	(0.279)	(0.0909)	(0.0827)
$\ln(GDPpc)^2$	-0.0339	0.0644	0.0493***	0.00626
	(0.0768)	(0.0687)	(0.0137)	(0.0126)
$\ln(Population)$	-0.00273		-0.00137	
	(0.00685)		(0.00676)	
Schooling	-0.00550		0.00740	
	(0.00797)		(0.00773)	
Skilled		-0.00382***		-0.00298*
		(0.00107)		(0.00144)
Semi Skilled		-0.00146		-0.00232*
		(0.00146)		(0.00130)
Share "White"		-0.000496		-0.000522*
		(0.000351)		(0.000297)
Informality		0.00191**		0.000204
		(0.000756)		(0.000462)
Share Agric		0.448***		-0.355**
		(0.123)		(0.145)
Urbanization		0.00165***		0.00134
		(0.000435)		(0.00101)
Share Imports		0.00148		-0.0732
		(0.0816)		(0.0692)
Share Exports		-0.0160		-0.0786
		(0.0684)		(0.0510)
Constant	0.336	0.420	0.826***	0.453***
	(0.442)	(0.307)	(0.143)	(0.110)
Observations	72	64	171	152
R^2	0.118	0.635	0.526	0.743
Adjusted R^2	0.0367	0.550	0.508	0.721

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22: Rural and Urban States, Fixed Effects, Using Gini (RAIS)

	Dependent Variable: Gini (RAIS)			
	Rural		Urban	
	(1)	(2)	(3)	(4)
ECI	0.00167	0.00136	-0.000394**	-0.000467**
	(0.00161)	(0.00214)	(0.000182)	(0.000212)
ECI^2	3.86e-05	5.05e-05	1.18e-06	1.66e-06
	(4.78e-05)	(6.95e-05)	(9.80e-07)	(9.63e-07)
$\ln(GDPpc)$	-0.239	-0.314	-0.223*	-0.409***
	(0.194)	(0.238)	(0.115)	(0.137)
$\ln(GDPpc)^2$	0.0333	0.0429	0.0322	0.0688**
	(0.0388)	(0.0478)	(0.0194)	(0.0239)
$\ln(Population)$	-0.0557		0.0216	
	(0.0354)		(0.0338)	
Schooling	0.00207		-0.00540	
	(0.00460)		(0.00386)	
Skilled		0.000862		-0.000314
		(0.00287)		(0.000677)
Semi Skilled		3.39e-05		-0.000407
		(0.00166)		(0.000734)
Share "White"		3.85e-05		0.000824
		(0.000491)		(0.000524)
Informality		-0.000529		-6.69e-05
		(0.000553)		(0.000380)
Share Agric		0.261		0.180
		(0.194)		(0.272)
Urbanization		0.000464		-0.000406
		(0.000413)		(0.000268)
Share Imports		-0.111*		-0.0163
		(0.0523)		(0.0261)
Share Exports		-0.0493		-0.0347**
		(0.0405)		(0.0141)
Constant	1.656***	0.937**	0.538	1.060***
	(0.421)	(0.288)	(0.446)	(0.209)
Observations	72	64	171	152
R^2	0.679	0.727	0.404	0.554
Adjusted R^2	0.650	0.663	0.383	0.515
Number of code	8	8	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix V: Technology Proxy

Table 23: Technology Proxy, Pooled OLS and Fixed Effects

	Dependent Variable: Gini					
	Pooled OLS			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
ECI	0.00150**	0.00166**		0.000249	0.000393	
	(0.000633)	(0.000637)		(0.000313)	(0.000360)	
ECI^2	-1.11e-05**	-1.20e-05**		-1.43e-06	-9.13e-07	
	(4.44e-06)	(4.70e-06)		(1.31e-06)	(1.67e-06)	
$\ln(GDPpc)$	-0.261***	-0.253***	-0.293***	-0.0879	-0.0452	-0.0540
	(0.0645)	(0.0629)	(0.0612)	(0.0814)	(0.0955)	(0.0932)
$\ln(GDPpc)^2$	0.0522***	0.0514***	0.0573***	-0.00532	-0.00835	-0.00724
	(0.0114)	(0.0109)	(0.00975)	(0.0140)	(0.0192)	(0.0188)
$\ln(Population)$	-0.00210	-0.00165	-0.00670	-0.0359	-0.138*	-0.140*
	(0.00412)	(0.00455)	(0.00489)	(0.0448)	(0.0730)	(0.0709)
Schooling	-0.0201***	-0.0210***	-0.0165**	-0.00605	-0.000933	-0.000156
	(0.00426)	(0.00466)	(0.00793)	(0.00680)	(0.00486)	(0.00483)
Technology		-0	0		-0	-0
		(0)	(0)		(0)	(0)
Constant	1.028***	1.014***	1.113***	1.392**	2.832**	2.870**
	(0.0883)	(0.0896)	(0.106)	(0.648)	(1.067)	(1.037)
Observations	243	210	210	243	210	210
R^2	0.528	0.554	0.472	0.469	0.410	0.407
Adjusted R^2	0.516	0.539	0.460	0.456	0.389	0.393
Number of code				27	27	27

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1