Anti-money laundering efforts – failures, fixes and the future

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Manuscript committee: Prof. dr. G.H. Addink
Prof. dr. V. van Kommer
Prof. dr. S. Rosenkranz
Prof. dr. E. Stam
Dr. U. Turksen

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Anti-money laundering efforts – failures, fixes and the future

Aanpak van witwassen: obstructies, oplossingen en ontwikkelingen
(met een samenvatting in het Nederlands)

Proefschrift

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door

Ioana Sorina Deleanu

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Promotoren: Prof. dr. B. Unger
Prof. dr. F.G.H. Kristen

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“The real voyage of discovery consists not in seeking new landscapes, but in having new eyes.” (Marcel Proust)

To my “Dutch parents”
Anneke and Bart van Steenbergen

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I believe a PhD is made of beliefs not barriers, it is made of all the obstacles cleared, not just the ones you see in the final print, and it is made of many, not just one author. Mine certainly is no exception. I wrote this PhD in little over four years, and I certainly would not have done it without the many support groups I had: my supervisors Prof. dr. Brigitte Unger and Prof. dr. François Kristen, my colleagues, my friends, and my family.

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Ioana Sorina Deleanu

September, 2015; Utrecht

Table of contents

List of abbreviations

AML	Anti-Money Laundering
CDA	Currency Demand Approach
DDOS	Distributed Denial of Service
ECB	European Central Bank
ECOLEF	Economic and Legal Effectiveness of Anti-money Laundering and Combating Terrorist Financing Report
FATF	Financial Action Task Force
FBI	Federal Bureau of Investigation
FinCEN	Financial Crimes Enforcement Network
FIU	Financial Intelligence Unit
FUR	Follow-up Report
IMF	International Monetary Fund
MER	Mutual Evaluation Report
PPO	Public Prosecutor's Office
UNODC	United Nations Office on Drugs and Crime

List of figures and tables

Figures

Tables

Foreword

This thesis reflects the knowledge that I have accumulated during the time of my PhD. As such, not only does it reflect my personal capacity to analyse data and critique the literature, but also the influence of the research groups within Utrecht University to which I belong, and the influence of the practitioners in the field of money laundering that I consulted in this time. Chapter 1 is co-authored with Joras Ferwerda and Brigitte Unger. Chapter 4 is co-authored with Radu Serban and Brigitte Unger.

Consequently, this thesis appeals to both academics and policy makers working in the field of anti- money laundering (AML). As such, academics may be drawn, in particular, to the exercises conducted in chapters 1 and 4. Conversely, practitioners and policy makers may be drawn, in particular, to the analyses and to the solutions proposed in Chapters 2 and 3.

Finally, the work presented in this thesis is just the initial step towards my overarching research goal to contribute to a better understanding of the dynamics that govern financial crime, while advancing organizational and strategy theories that can improve the decision making of practitioners and policy makers engaged in countering financial crime.

Introduction

Originated in the US in the second half of the 20th century, the fight against money laundering has fundamentally changed the global financial landscape and has redesigned international crime fighting, at an unprecedented pace. There are many reasons for which money laundering has enjoyed so much of a prominent role on the international and domestic agendas in the past 30 years. Widespread concerns on the scale and scope of organized crime – at first on drug trafficking and later, also on fraud and tax evasion and other offences – pressured politicians and academics alike to look for solutions. And after such solutions were found, the political and legal engagements to fight crime by depriving criminals of their ill-gotten gains were motivated by the intrinsic belief of norm setters that these solutions were also effective. Fuelled by concerns and beliefs, large amounts of resources (public and private funds, expertise, intelligence and man hours) have been allocated to designing rules and norms that enabled law enforcement organizations to trace, seize and confiscate criminal assets. Only at the European Union (EU) level, four Anti-Money Laundering (AML) Directives were developed in order to harmonise the money laundering offences and other AML rules. And, perhaps the most dramatic impact of these global political and legal engagements was the creation of a system of agencies entrusted with fighting money laundering that would be active and decisive at every level of financial and criminal governance: the money laundering reporting officers at the micro level, the Financial Intelligence Unit (FIU) at the mezzo level, and the Financial Action Task Force (FATF) and Moneyval at the macro level.

Since their creation, AML efforts have been analyzed extensively, both by economists and by lawyers. The effectiveness and the legitimacy of the measures taken to fight money laundering have received the most interest. Notable works include the comparative legal study of the effectiveness of AML regulation against the backdrop of due process of Stessens (2001), the comparative legal study of the effectiveness of supervision in AML matters in Europe of Van den Broek (2015), and theoretical and econometric studies on the effectiveness and the legitimacy of the "carrot and stick" approach to fighting money laundering in the absence of carrots of Masciandaro and Portolano (2004), Takáts (2007), Unger and Ferwerda (2008) and Unger and Van Waarden (2009).

My contributions address important topics in the debate on and the organisation of the AML efforts, which are related to the legitimacy and the effectiveness of AML policies. This thesis provides a reflection on the assessments of concern that trigger policy makers working in the field of crime fighting. It also provides an assessment of the effectiveness of the agencies

entrusted with fighting money laundering at a national level and, of the country blacklisting of the FATF. Central to this thesis stand the acknowledgement that information is pivotal to fighting money laundering, and the hypothesis that an analysis that internalizes the behavioural critiques of the rationality assumption, and that explores the boundaries of the principle of methodological individualism[1] can offer a more accurate picture of the failures, fixes and the future of the AML efforts. Finally, this thesis contributes to the understanding of the social norms and of the psychological and network effects that affect human action, in the context of crime and countering crime, with the intention of designing better AML solutions and assessing their effectiveness.

1. A multi-angle approach to studying anti-money laundering efforts

Countering money laundering requires global thinking while remembering that the devil often lies in the national details. Legal studies on AML policies need, by the very nature of the subject, to take a broad perspective, while at the same time, to zoom in on national practices. Nevertheless, traditional legal research discusses and compares legal principles attributed to one or more legal families, without focusing on the application and the interpretation of these principles in each country. Applied legal scholars, on the other hand, often look at a single judicial system or explore a comparison of a select few judicial systems. As such, the latter' analysis is coined to a limited number of countries owing to the difficulties associated with data collection, as well as, with the aggregation of their results. Secondly, one must recognize that the information asymmetry that shields criminals from the vigilant eye of law enforcement has as much to do with criminals' behaviour, as it has to do with the inefficiencies plaguing law enforcement coordination, with the political processes underpinning the statistics on money laundering and with the potential tolerance to this gentleman's sport, that society expresses. Yet economic scholars rely heavily on official statistics, thereby inherently trusting that observations are objective representations of the truth, as opposed to socially constructed events that may, in fact, result from the very prognostical nature of economics. It is therefore, my belief that by taking on a law and economic perspective, while, at the same time, recognizing that the behaviour of criminals, as well as of norm setters is psychologically determined and influenced by their social context, we will be able to better understand money laundering and to design better solutions to counter it.

[1]The principle of methodological individualism states that social outcomes should be explained by focusing on the individual as the operative unit of analysis without a normative embrace of individualism or any ontological conclusion about the place of the individual in society (Ahdieh, 2011).

While money laundering is ubiquitously understood as *"the processing of criminal proceeds to disguise their illegal origin",*[2] combating money laundering is conceptualized differently across disciplines. Nevertheless there is a general agreement that information is the crucial starting point in combating money laundering. Economic scholars thus, view acquiring intelligence as means to reduce the informational asymmetry that exists between law enforcement and money launderers (*Cf*. Masciandaro and Portolano, 2004; Masciandaro, 2007; Takáts, 2007; Unger & Van Waarden, 2009). Law enforcement agencies need to gather information in order to bring sufficient evidence to the courts to allow for criminal convictions for money laundering, thus they are in need of adequate functioning legal rules and norms and sufficient technical, physical and human resources (*cf*. Spencer, 2002). Consequently, evaluations of efficiency and legitimacy revolve around information: does the intelligence the law enforcement agencies receive from the reporting entities yield investigations and convictions on money laundering (ECOLEF, 2013)? Does the number of convictions justify the high reporting costs borne by the financial sector (Unger & Van Waarden, 2009; Takáts, 2007)? Does it justify the loss of privacy (*cf*. Schott, 2006; Stessens, 2001)?

Accordingly, this is a study of the informational topics that are related to current AML efforts. As such, it is a study that recognizes that information has a special treatment across the disciplines. Furthermore, it explores the legal and economic implications of the behaviour of individuals whose rationality and willpower are bounded. And finally, this study seeks to reach towards the limits of the principle of methodological individualism in hope for a richer account of law and economics.

2. Information and its treatment across disciplines

The interpretation of information ranges from a measure of non-randomness contained in a message which is likely to generate knowledge, to a universal meaning contained by a unit of informational commodity. Information can be made scarce by the legal arrangements put in place and it can limit our actions while enabling us to take decisions. Consequently, when studying the role of information in the context of money laundering and of combating money laundering, we need to be able to navigate through the different concepts of information and use them appropriately.

According to the Oxford English Dictionary, the basic meaning of information is the *"disclosure of knowledge in general"*. If related to data, it means *"that which is obtained from processing of data"*. In a legal context, information is defined as *"a statement in which a magistrate is*

[2] Definition of the Oxford English Dictionary is "the process of concealing the origins of money obtained illegally by passing it through a complex sequence of banking transfers or commercial transactions", available at http://www.oed.com/view/Entry/121171?redirectedFrom=money+laundering#eid36244231

informed that a named person has committed a stated offence and a summons or warrant is requested"[3] and finally, mathematically speaking, information is *"a mathematically defined quantity […] which represents the degree of choice exercised in the selection or formation of one particular […] message, out of a number of possible ones, and which is defined logarithmically in terms of the statistical probabilities of occurrence of […] the elements of the message".*[4]

As Schauer and Wise (1997, p.1095) stated, *"in making their decisions, legal decision-makers rely on information about the existence of norms, and information about the existence of facts".* In a criminal law context, information is needed for prosecution to stand up to its burden of proof (*cf*. Spencer, 2002). For this purpose, norm setters design a single ethical buyer (hence owner) of criminal information – the state, through its law enforcement agencies – and sanction failure to report. The intricacies associated with the ownership of information[5] are particularly relevant in the case of the fight against money laundering. As information becomes "de-commoditised" – no longer equating with criminal evidence but with potential knowledge drawn from data processing or suspicion – the state loses the legitimacy of being the sole buyer of this information. What would originally expand the scope of information received by law enforcement had, as unintended consequence, in fact, the limitation thereof, in states that experienced traumatic state surveillance during and after the Second World War.[6]

As opposed to the legal sphere, where the controversy related to information is its regulation, the main controversy in economics related to information is its treatment as scarce commodity and simultaneously as non-scarce component of the decision making mechanism (*Cf*. Spence, 1974 and Boyle, 1992). In economics, information is seen as the opposite of uncertainty (*cf*. Arrow, 1996) and game theory is used to explore different strategies and equilibriums associated with different levels of uncertainty. The manner in which information is incorporated into the decision making process gave rise to two opposing views: orthodox and heterodox economics. While traditional orthodox economics is framed in the "rationality,

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[3]These interpretations of information are not exclusive to the above named fields. For instance, Kristen (2004) adhered to a definition of information that related to data processing in the context of a legal study on insider trading: *"[…] information relates to the meaning that is being allocated to data in the context of general/ personal knowledge, experience and circumstances, as well as other data, once the data is known. Information can thus be gained by consulting data".* (p.857)

[4] Oxford English Dictionary (retrieved from *www.oed.com/view/Entry/95568?redirectedFrom=information#eid*)

[5] Boyle (1992) argued that, in general, the regulation of, the commoditization of, and access to information is decided on the basis of two often subjective arguments. The first referred to the public/ private nature of information and the second related to the compensation of the author's genius. He argued that the many contradicting legal treatments of information were, in fact, generated by the subjective activation of these arguments (Boyle, 1992, p.1418).

[6] For instance, the French Financial Intelligence Units – the law enforcement agency that is entrusted with receiving information on money laundering – could not start investigation on own motion. Furthermore, laymen not falling under any law obliged category cannot report to this FIU directly on suspicion of money laundering (ECOLEF, 2013, pp.155-156).

individualism, equilibrium" paradigm, the more novel heterodox economics is framed in the "institutions, history, social structure" paradigm (*Cf*. Davis, 2006). Orthodox economics views economic agents as rational decision making individuals who are able to process information consistently such that they are always able to judge the utility of actions and goods and therefore behave predictable from a utility maximizing point of view (*cf*. Samuelson & Nordhaus, 2001). Heterodox economics, on the other hand, assumes that social reality is intrinsically dynamic, organically structured and includes polyvalent interpretations of information (Lawson, 2006). Therefore, individual psychological framings determine the actual usage and valuation of information in decision making and social networks affect information transmission and, in turn, shape individual and collective decisions (Davis, 2006).

Subsequently, law and economic scholars aim at solving the legal controversy with the help of economic tools of reasoning (*Cf*. Kitch, 1983). Law and economic scholars use economic tools and reasoning to construct consistent and justifiable legal practice that, in turn, will support economic efficiency and improve market conditions.[7] Their interest shifts from the philosophical exploration of the law - namely of the limits to controlling society by managing this information, the scope for punishment for money -laundering, the coherence of the law, and the allocation of responsibility to report if in possession of knowledge of a money laundering crime to different societal groups – to how law in practice can promote economic efficiency by recognizing the valuable information and by managing it effectively (*cf*. Giesen & Kristen, 2014).

Finally, from a mathematical point of view, information is viewed as the measurable distance from absolute randomness of a choice of symbols and of their ordered succession. As a result, information is the opposite of uncertainty. Entropy is a measure of the non-randomness contained in a message. One of the most well-known entropies, Shannon's entropy, proposes a measure of the potential information contained in a message that equals the probability that this message surprises, given that it is coherent and understood (Shannon, 1948). Although both measure uncertainty, Shannon's entropy and neoclassical economists' quantification of information, are not similar. The reason for this is that the former allows for the full incorporation of the inter-relations between economic and communicatory processes (*Cf*. Babe, 1993, p.53) and in this sense is a much rich measure of uncertainty.

[7] Internet Encyclopedia of Philosophy (Internet Encyclopedia of Philosophy) (retrieved from www.iep.utm.edu/law-econ/)

3. Methodological foundations

Under the circumstances described above, in this PhD thesis I take a law and economics perspective to the study of the information underpinning the AML efforts. Essentially, I used economic tools in order to construct justifiable legal practice that in turn promotes economic efficiency. For this reason, I tried to approach money laundering and AML efforts from a realistic model of decision making – one that is subject to limited rationality and social influence.

Traditionally, the discipline of law and economics is built on two fundamental principles that are borrowed from the economic science: the principle of rationality and the principle of methodological individualism (*Cf*. Ellickson, 1998; Ahdieh, 2011). Yet, the limits of the principle of rationality are extensively explored by behavioural economics as *"law is a domain where behavioural analysis would appear to be particularly promising in light of the fact that nonmarket behaviour is frequently involved"* (*Cf*. Jolls, Sunstein & Thaler, 1998, p.1473). Especially with respect to information, a very fruitful symbiosis exists between law and behavioural economics, in particular because the latter branches of economics explore strategic thinking and human limits to mean-end rationality (*Cf*. Jolls, Sunstein & Thaler, 1998). Furthermore, in 1994, Kenneth Arrow challenged his fellow economist's devotion to the principle of methodological objectivism, by arguing that *"even the most standard economic analysis shows that social categories are in fact used in economic analysis all the time and that they appear to be absolute necessities of the analysis, not just figures of speech that can be eliminated if need be"* (Arrow, 1994, p.1). As a consequence, the second pillar of law and economics started to be challenged as well. In particular, with respect to information, introducing social norms and network externalities, recognizing the role of interdependences in shaping human action next to their preferences, is thought to *"lead us to a richer account of law and economics"* (Ahdieh, 2011, p.44).

This PhD thesis adheres to the literature of law and economics, while trying to approach the analysis of money laundering from a conception of choice that reflects human behaviour as real as possible. Essentially, this thesis builds on the premises that AML policies are socially embedded, that a money launderer's sentiment is socially founded and psychologically bounded and that our understanding of the effectiveness of AML efforts will benefit from an explicit consideration of these premises.

4. Thesis outline and overview

In this PhD thesis I explored the different conceptualizations of information that surface in the discussion of AML policies and in their subsequent effectiveness and legitimacy evaluations. Furthermore, I conducted this exploration having internalized the behavioural critiques of the rationality assumption and often at the boundaries of the principle of methodological individualism. And, finally, as the Figure below shows, I addressed the AML policy chain, from the analysis of the threat, to the functioning of the policy, to the effectiveness of the evaluations, to the use of a platform for money laundering purposes.

Four independent studies compose this PhD thesis. The first study looks at one of the core methods to estimate the underground economy, and argues for a behavioural change in the theoretical micro-foundations of this method. The study contends that by recognizing the psychophysical limitations of tax payers we are in a better position to measure the cash based underground economy and explain why, in some cases, the seminal measurement method of Tanzi (1983) is not applicable. Subsequently, the second study explores how the value of information is modified when transmitted hierarchically among institutions that play a role in the fight against money laundering. The study argues that by recognizing the role of institutional distance in the framing of communication between law enforcement organizations, we can enhance our capacity to measure and address the issue of effective cooperation. The third study is built on the behavioural finding that individuals perform badly at generating random numbers and maintains that international evaluations on performance may trigger strategic tamperings with national statistics on money laundering. The study reflects on the effectiveness and legitimacy of the naming and shaming strategy that countries are subject to, when statistics are not objective representations of the truth. Finally, the fourth study looks at what may be the future of money laundering in the age of anonymous digital currencies. This study argued that if we recognize that individuals address uncertainty by relying on the common pool of experiential knowledge, then, the dynamics of the wisdom of the crowds may help us better anticipate future social outcomes, among which the global usage of BITCOINs for criminal purposes.

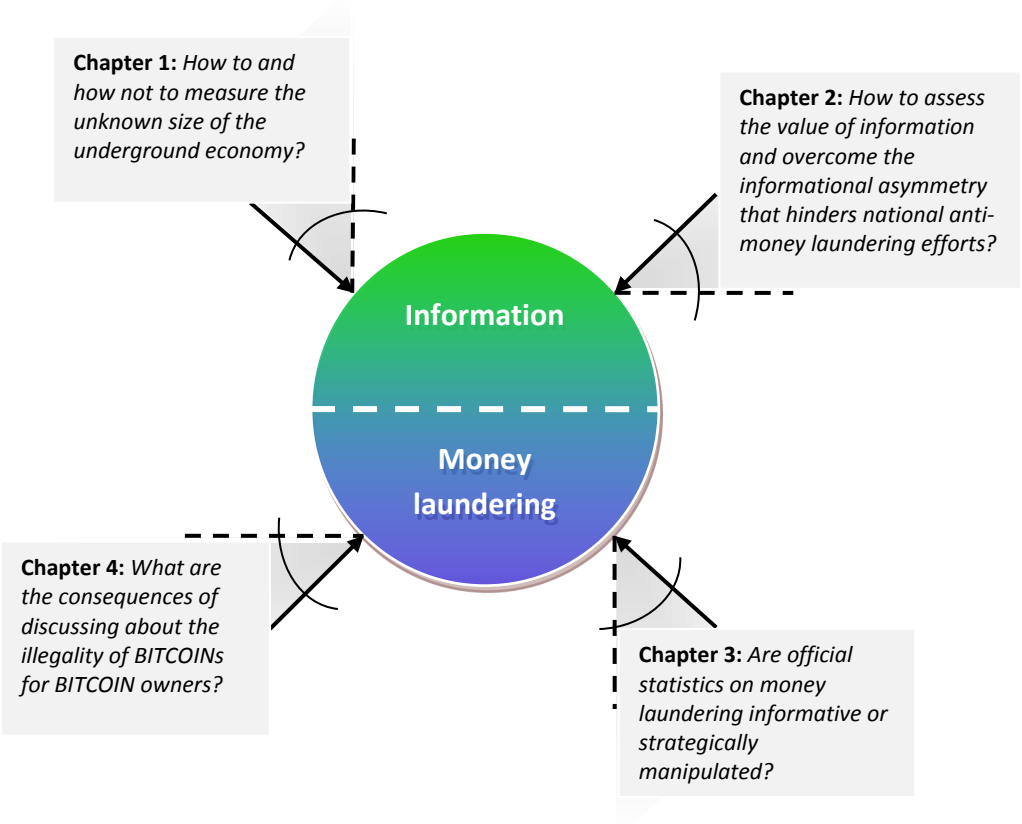

Figure: A graphical description of the multi-angle exploration of information based AML efforts [8]

The Figure above illustrates four angles that form the multi-angle exploration of information in the context of AML efforts as well as the core message contained in the four studies that make up this thesis. These four studies are summarized below.

Study 1: Re-evaluating Tanzi's Currency Demand Approach (CDA) to Estimate the Underground Economy

Measuring money laundering – the amount of money derived from a criminal activity that is thereafter given an apparent legitimate origin – is a study in its infancy. Many estimates of stocks of money laundered are characterized either by vague calibrations, little disclosure on

[8] I owe this exposition to François Kristen.

the methodology or substantial inconsistencies (*cf.* Unger & Rawlings, 2008). Just as money laundering, estimating the size of the underground economy – the place where criminals meet tax avoiders and helping neighbours outside the vigilant eye of governmental authorities – is a study in its infancy that has creates significant controversy for both scientists and politicians. The reason thereof is the ambiguity surrounding these two similar endeavours: one cannot observe the accuracy of the estimates. Measurements of the underground economy as well as of the stock of money laundered are, therefore, extremely sensitive to errors and to manipulations (*cf.* Tanzi, 1996). And, the association between measuring the underground economy and measuring the stock of money laundered does not stop here. Many of the econometric models used to estimate the volume of money laundered rely on measurements of the underground economy (*i.e.* Chong & Lopez-de-Silanes, 2007; Argentiero *et al.*, 2008; Ardizzi *et al.*, 2013; Buehn & Schneider, 2013) (*cf.* Levi & Reuter, 2006).

In this chapter, we revisited the literature on the underground economy and specifically Tanzi's (1983) seminal method to evaluate the underground economy. We particularly focused on the theoretical micro-economic foundations of Tanzi's model. While Tanzi assumed a linear relationship between taxes and the cash based underground economy, we hypothesized that, in line with the psychophysics literature, tax payers go underground only in reaction to a tax increase that overcomes their Weber fraction.

We tested this hypothesis by replicating Tanzi's model on the Eurozone dataset – a sample characterized by stable taxes, and found that taxes cannot explain the extra demand for cash Euros. Secondly, we extended the dataset used by Tanzi (1983) until 2006, and replicated his analysis while correcting for unit root. We found that the relationship between taxes and the demand for cash US dollars only holds between 1930 and 1960, when US personal income taxes varies from one year to the other, sometimes by as much as 70%. Additionally, in the subsequent decades, when personal income taxes stabilize, we found no significant influence of tax changes on the extra demand for cash US dollars. Finally, we reviewed a sample of contradictory empirical literature on the CDA and analyzed the size of the tax changes captured by each of these papers. In line with the law of diminishing sensitivity to sensory stimuli, we found that only large tax changes drive the excess demand for cash.

This chapter concluded that the relationship between taxes and the extra cash demand – a relationship that is so crucial to Tanzi's method – only holds in times of high tax volatility. This significant finding implies that Tanzi's method is not universally applicable, and that its otherwise universal application is likely to yield misleading estimations of the underground economy. In turn, this may lead to biases both in the design of national AML policies and in the cost and benefit and effectiveness analyses thereof.

Study 2: Effective information sharing – the undervalued component of the Anti-money laundering fight

The first AML legislation was born in 1986 in the US: the Money Laundering Control Act of 1986 (Pub. L. No. 99-570). In 1989 the FATF was founded by the G-7 in order to set international standards and thereby coordinate the global effort to combat money laundering. These global efforts were motivated by widespread concerns on the scale and scope of organized crime – at first on drug trafficking and later also on fraud and tax evasion and other offences – and by the intrinsic belief of norm setters that these solutions are also effective (*Cf*. Stessens, 2001). In the meantime however, several researchers (Stessens, 2001; Ross and Hannan, 2007; Takáts, 2007; Gelemerova, 2008; Dalla Pellegrina and Masciandaro, 2009; Unger & van Waarden, 2009) have stepped up questions about the real effectiveness of the AML policies. As convictions rates are seen as indicators of effective anti-money laundering policies (*cf*. Unger & Van Waarden, 2009), why is the number of convictions for money laundering in general so low and so different across countries?

This chapter is built on the assumption that there exists a social component that affects the valorisation of information when information is shared between organizations that are institutionally different. Consequently, I hypothesized that countries where the information about money launderers is more effectively dispersed among law enforcement agencies are more effective at repressing money launderers.

The analysis used the information diagrams built for the 27 EU Member States in ECOLEF (2013, p.164-220). On the basis of these diagrams I identified the main organizations involved in the AML efforts, the information links and the institutional distance between them. Inspired by the findings of network theory – namely that proximity matters for cooperation – I employed Shannon's (1948) theory of entropy to calculate the potential for information transmission given the institutional distance between the communicating organizations. The method I proposed for measuring the effective information sharing among authorities involved in the AML efforts, after suspicion is triggered, was based on minimizing the institutional distance between these organizations while approaching as many institutionally different organizations as possible.

Finally, I used pair-wise correlations and regression analysis to show that countries that share information better, have, all else equal, significantly higher recordings of convictions for money laundering. This relationship held also when correcting for the different levels of money laundering threat countries were exposed to. The second study thus, aims to demonstrate the importance of information sharing and a proper organisation of the information flow between law enforcement agencies, FIUs and other institutions involved in the AML strategy, in order to increase the effectiveness of the AML policy.

Study 3: Do countries manipulate official statistics on money laundering? Evidence using Benford's law

Conventional wisdom tells us that countries may strategically manipulate their official statistics. In some cases however, it is very clear that some countries have clear benefits from strategically manoeuvring their statistics. At the core of the current global AML strategy lays the FATF. The main role of this international watch-dog is to create standards of conduct vis-à-vis AML methods and to indirectly enforce them worldwide. Countries comply with the standards of the FATF and agree to be evaluated on their efforts to enforce and uphold these standards, fearing of otherwise being blacklisted – *i.e.* subjected to severe capital restrictions from the United States and from the latter's trade partners (Masciandaro, Takáts& Unger, 2007).

In this chapter I used a novel statistical test that is based on the distribution of the first digits of official statistics on money laundering (also known as Benford's law) to test the likelihood that European statistics on money laundering are strategically manipulated. The standard assumption is that without prior knowledge of Benford's law, since people are not intuitively good at creating datasets that follow Benford's distribution (*cf*. Camerer, 2003), data deviating thereof is likely to indicate irregularities. In light of the principal agent literature, I hypothesized that countries with higher cheating incentives have significantly more deviations in their official statistics, independent of their capacity to do good book keeping. To test this, I put together a dataset that reflects the latest European political thought processes pertaining to AML and pools together indicators of compliance and efficiency. This allowed for a meaningful comparison where Benford's law can be efficiently applied to uncover potential misreporting. I therefore gathered yearly statistics on money laundering from Eurostat, from national FIUs and from the Mutual Evaluation Reports (MERs) of the FATF or of Moneyval on 29 indicators from 2003 to 2010 for 27 EU Member States.

I found evidence that European statistics on money laundering were, according to Benford's law, to a great extent unreliable, and that countries reacted strategically to the international community's pressure to put the fight against money laundering on the top of their national agenda. This is an interesting finding in relation to that of Study 1 by which I found that an AML policy based on an estimation of the underground economy based on Tanzi's model ran the risk of overreacting, being too repressive, and imposing too high standards on the EU Member States. In turn, this study showed how the same member states might have generated statistics that provided for a better impression of their AML policy.

Study 4: What drives BITCOIN investment: legal, financial, or technological opportunities?

In 2008 the world was taken by surprise by a new concept – a new form of money called BITCOIN. Anticipated by the IT community and awaited by libertarian ideologists, BITCOIN's popularity among economists lies in its capacity to solve the fundamental problem of exchange without intermediaries (*cf*. Brito & Castillo, 2013). In a potentially irreversible paradigm shift, BITCOIN proponents suggested trusting publicly available algorithms instead of well-known financial intermediaries: the banks. The multi-facets of this paradigm shift – *i.e.* a higher degree of anonymity, systemic transparency, low transaction costs – next to the novelty induced instability and regulatory ambiguity, have almost immediately triggered opportunistic and frightening thoughts and emotions among the general public and regulators alike. Furthermore, many questions raised by BITCOINs have not been answered so far. For instance, what are BITCOINs used for? Are they tools for crime, financial solutions or technical solutions?

In this chapter, we examined how online information referring to BITCOINs influenced transactions volumes and the Dollar-to-BITCOIN exchange rate. We used computational linguistics to analyze 13,287 articles that Google returned on daily "BITCOIN" queries, to construct new measures of the composition and evolution of investor attention to the BITCOIN discourse. These measures reflected investor attention to the legal, financial and technological threats and opportunities of BITCOINs. We used these new text-based measures to test hypotheses about the behaviour of BITCOIN investors and, simultaneously, to distinguish different BITCOIN user groups as well as their main sources of information.

The central finding of this chapter is that BITCOIN investors trading on financial markets reacted to financial and technological information published on BITCOINs by adjusting their trading activity. Furthermore, BITCOIN investors that mostly transacted in BITCOINs (*i.e.* outside stock exchanges thus) reacted only to legal/ illegal information, again by adjusting their transaction activity accordingly. This suggests that while traders on the stock exchange are interested in BITCOIN speculation, BITCOIN owners that transact for goods and services outside the stock exchanges are interested in the legal/ illegal component of BITCOINs. Importantly, with this research, we showed that it is possible to capture some of the basic interests behind the BITCOIN market even in the presence of anonymity. We further showed that it is possible to identify the key signal givers for the BITCOIN market, as well as the impact of their signals on market participants.

BITCOINs are thought to offer criminals and tax avoiders a platform to transfer wealth at a low cost and particularly with a high degree of anonymity. It is the same anonymity that in combination with the cross border operation of the BITCOIN market will hamper law

enforcement agencies to effectively gather information about money laundering transactions. Having this in mind, it becomes ever more important for information to be effectively circulated among law enforcement after suspicion has been triggered, as Study 2 shows.

5. Concluding remarks

I started my research on the topic of money laundering under the auspice of an impressive set of political and legal engagements to fight crime by depriving criminals of their ill-gotten gains, that originated in the US in the second half of the 20th century, and that have fundamentally changed the global financial landscape and redesigned international crime fighting.[9] I soon realized that information is pivotal to fighting money laundering, as many, if not all of the research questions asked involved the concepts "knowledge", "information", "data" or "intelligence" (*e.g.* What will reduce the information asymmetry between money launderers and law enforcement (*cf*. Masciandaro & Portolano, 2004; ECOLEF, 2013)? How is the information collected by law enforcement organizations turned into cases and convictions (*cf*. ECOLEF, 2013)? Do the results justify the loss in privacy and the costs of delivering the information (*cf*. Schott, 2006; Stessens, 2001; Unger & van Waarden, 2009)?). Building on the seminal works of Tanzi (1983), Stessens (2001), Unger & van Waarden (2009), Takáts (2007) and Masciandaro (2007), I therefore explored the information that underpins AML efforts and its treatment across disciplines. And in this endeavour I acknowledged that human rationality is bounded and attempted to reach towards the limits of the principle of methodological individualism, in hope for a richer account of law and economics.

My contributions address important topics in the debate on and the organisation of the AML fight, which are related to the legitimacy and the effectiveness of AML policies. This thesis provides a reflection on the assessments of concern that trigger policy makers in the field of crime fighting, and an assessment of the effectiveness of the agencies entrusted with fighting money laundering at a national level, and of the country blacklisting of the FATF. In doing so, I seek to surpass the principle of methodological individualism of law and of economics and to examine how a series of psychological, institutional and sociological factors affect money laundering decisions, AML solutions and their implementation, and, in turn, the effectiveness of AML efforts. Essentially, this thesis builds on the premises that AML policies are socially embedded, that a money launderer's sentiment is socially founded and that our

[9] Updated overviews of the legislation and relevant bodies that play a role in the global AML strategy is the United Nations Instruments and International Standards (UNODC) (retrieved from www.unodc.org/unodc/en/money-laundering/Instruments-Standards.html?ref=menuside) and the International Monetary Fund (IMF) Anti-Money Laundering/Combating the Financing of Terrorism (AML/*CF*T) - Reference Materials, Research and Publications (AML/*CF*T Reference Materials, Research and Publications) (retrieved from www.imf.org/external/np/leg/amlcft/eng/aml4.htm)

understanding of the effectiveness of AML efforts will benefit from an explicit consideration of these premises.

In this thesis I conducted a multidisciplinary exploration of information in the context of national and supra-national AML efforts. The findings of the four studies composing this thesis have implications for both the legitimacy and the effectiveness of the AML fight. As such, Study 1 reflected on the correct use of the Tanzi model in estimating the underground economy and on the risk of inaccurately valuing the need for and scope of an AML policy. Subsequently, Study 3 demonstrated that countries are willing to strategically tamper with their official statistics in order to comply with the high standards set by FATF. In my view, this trend risks distressing any policy based on such statistical evidence and casts doubt on current valuations of the effectiveness of present AML policies. Furthermore, concerning the effectiveness of the AML efforts, Study 2 argued that once suspicion is triggered, the extent to which information is shared among national agencies entrusted with the repression of money laundering matters for the actual securing of convictions. I believe the EU Member states can learn from each other, and best practices are easily implemented. Moreover, there is a growing need to improve the cooperation between law enforcement agencies, if as Study 4 inferred, financial criminals understand and use BITCOINs for the (fully) anonymous transfer of wealth.

Summing up, what could be more interesting and engaging than writing a PhD thesis on money laundering in the political and economic climate of 2010-2015? This is time when BITCOINs – a revolutionary currency that promises individual anonymity and systemic transparency crystallized,[10] a time when Europol revealed large-scale match fixing and illegal gambling taking place in world class football,[11] a time when WikiLeaks and Edward Snowden revealed how our privacy is breached daily by intelligence services around the globe,[12] a time when investigative journalists revealed how the rich multinationals paid hardly any taxes,[13] a time where a new European AML Directive that directly addresses tax crimes took shape.[14] In this context, one may rightfully wonder: Why has crime and crime fighting had such marginal role in economics?

[10] BITCOIN Definition (Investopedia) (retrieved from www.investopedia.com/terms/b/bitcoin.asp)
[11] Results from the largest football match-fixing investigation in Europe (Europol Update) (retrieved from www.europol.europa.eu/content/results-largest-football-match-fixing-investigation-europe)
[12] Edward Snowden: Leaks that exposed US spy program (BBC News) (retrieved from www.bbc.com/news/world-us-canada-23123964)
[13] Tax Probe Targets U.S. Firms (WSJ) (retrieved from www.wsj.com/articles/eu-to-probe-tax-affairs-of-apple-starbucks-1402476699)
[14] EUR-Lex Access to European Union law (EUR-Lex) (retrieved from eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52013PC0045)

Chapter 1 – Re-evaluating Tanzi's Currency Demand Approach to Estimate the Underground Economy

This study is co-authored with Joras Ferwerda and Brigitte Unger.

1. Introduction

Measuring money laundering – the amount of money derived from a criminal activity that is thereafter given an apparent legitimate origin – is a study still in its infancy. Many estimates of stocks of money laundered are characterized either by vague calibrations, [15] little disclosure on the methodology or substantial inconsistencies.[16] Just as money laundering, estimating the size of the underground economy – the place where criminals meet tax avoiders and helping neighbours outside the vigilant eye of governmental authorities – is a study in its infancy that has created significant controversy for both scientists and politicians. The reason thereof is the ambiguity surrounding these two similar endeavours: one cannot observe the accuracy of the estimates. Measurements of the underground economy as well as of the stock of money laundered are, therefore, extremely sensitive to errors and to manipulations (*cf.* Tanzi, 1996). The association between measuring the underground economy and measuring the stock of money laundered does not stop here. Many of the econometric models used to estimate the volume of money laundered rely on measurements of the underground economy (*i.e.* Chong & Lopez-de-Silanes, 2007; Argentiero *et al.*, 2008; Ardizzi *et al.*, 2013; Buehn & Schneider, 2013) (*cf.* Levi & Reuter, 2006). Reviewing the seminal method to evaluate the underground economy – Tanzi's (1983) Currency Demand Approach (CDA) – is therefore needed to ensure the consistency of the estimates of both the underground economy and of the stock of laundered money. Furthermore, and equally important, a regular review of the methods, definitions and data used in the above mentioned estimation exercises may narrow down the large estimation error bandwidths. This in turn would ensure the support and legitimacy of the recent politically induced efforts to combat money laundering and other financial crimes (*Cf.* Walker & Unger, 2009).

[15] One of the most quoted estimates is the 2-5% of global GDP 'guesstimate' of Michel Camdessus, Director of the International Monetary Fund (available at www.imf.org/external/np/speeches/1998/021098.htm)

[16] Notable reviews of national and global estimates and of the challenges associated to this exercise are given by Reuter and Truman (2004), Unger and Rawlings (2008) and Barone and Masciandaro (2008).

Tanzi (1983) argued that taxes are a main determinant of the underground economy and businesses wishing to remain unseen by the government would use cash to do so. Specifically, he showed that taxes could explain the extra cash demand for US dollars and, assuming that cash in the underground economy had the same velocity as cash used in the legitimate economy, he was able to give an estimate for the underground economy and of its development. However controversial the method, it is one of the most influential studies on estimating the shadow, or underground economy. Moreover, Tanzi's method is subsequently used as scaffold for other models (*e.g.* Schneider & Enste, 2002; Bajada, 1999) whose estimates of the shadow economy have even triggered the correction of official GDP statistics (The Organisation for Economic Co-operation and Development (OECD), 2011, pp.14-16).

By revisiting the literature on the underground economy and, specifically, the Tanzi (1983) model, we looked at whether the CDA is still a viable method to estimate the underground economy, and under which circumstances. Our hypothesis is that tax payers go underground only in reaction to a tax change that overcomes their Weber fraction – that is, in reaction to a tax that stimulates them to react accordingly. In order to test this, we replicated Tanzi's model on Eurozone data, a sample characterized by stable taxes. We then extend the US sample of Tanzi until 2006 and reran his analysis. Thirdly, we tested our hypothesis on a sample of empirical works that estimated various underground economies via the CDA and yielded contradictory results. While the sample of empirical works was very small, it supported our hypothesis. We concluded that the relationship between taxes and the extra cash demand only held in times of relatively high tax volatility.

The finding that the relationship between taxes and the extra cash demand – a relationship that is so crucial to Tanzi's method – only held in times of high tax volatility is of utter importance. This would imply that Tanzi's method is not universally applicable, and that its otherwise universal application is likely to yield misleading estimations of the underground economy. Finally, our efforts have broader implications for research in social sciences, since it supports the merits of replication studies. This is in line with the work of Dewald, Thursby and Anderson (1986), who strongly encouraged replication studies in the field of finance and banking, and with the works of Hamermesh (2007) and Naumovska (2014) who emphasized the role of replications in economics and management in general.

This chapter unfolds with an overview of the literature on estimating the underground economy. Section 3 introduces the psychophysics literature and the hypothesis to be tested. Section 4 reports on the data used to test Tanzi's method. Section 5 presents the results of our analysis and section 6 concludes that the CDA, as constructed by Tanzi (1983), only held in times of large tax changes, and that it should therefore be used only in these circumstances, as otherwise it may give misleading estimates of the size of the underground economy. Finally, it is important underline that this study reviews a method used primarily in the

estimation of the underground economy. Therefore, we will not focus on the implications that the findings have for estimating money laundering.

2. Literature review

2.1. Confusing definitions of what is being measured

Owing to all the unknown parameters that surround the underground economy and because of the explicit efforts of those involved therein to maintain obscurity and ambiguity, the size of the underground economy remains hard to *define and measure.*

Unfortunately, the literature uses quite ambiguous terms for the underground economy and its relation to tax evasion. Terms like the "underground" economy, the "shadow" economy, the "black" or "grey" economy, the "hidden" economy, the "subterranean" economy, the "informal" economy, the "unrecorded" economy, the "unreported" economy, the "second" economy and the "unobserved" economy are still often used rather arbitrarily (*cf*. Feige, 1990). Depending on the classification scheme they include regular activities such as helping neighbours, irregular activities such as illicit labour, and illegal activities like drug dealing and value added tax fraud. When it comes to tax evasion, the classification schemes seem to offer us an abundance of choice: is tax evasion part of the shadow economy (Enste & Schneider, 2006) or of the underground economy (Schneider & Enste, 2000)? Or doesn't it belong to the shadow and/or underground economy at all, as suggested by Schneider and Enste (2002)? Or is it irrelevant to distinguish between all these terms? Though each of the classification schemes depends on different criteria which makes the distinctions above partly understandable, there is clearly confusion in terminology. This confusion in definitions also shows in what is being measured. For Schneider and Enste (2002) the informal sector comprised activities which were not part of national income accounting. These included, apart from regular activities such as helping ones neighbour, irregular and criminal activities. The shadow economy is defined by irregular activities (for example illicit labour), and the underground economy is defined by criminal activities. According to this view, tax evasion is neither part of the formal nor part of the informal sector, because it does not produce any added value. For this reason, Schneider and Enste (2002) also explicitly criticized the demand for cash approach, which dealt with tax evasion and to which Tanzi's model belonged, for overestimating the shadow economy. Contrary, in Enste and Schneider (2006, p.37) tax evasion was given as an example of activities belonging to the shadow economy as opposed to drugs and fencing, which were listed as examples for the underground economy. In the rest of this chapter we use the term which Vito Tanzi uses – the underground economy, and as such, *encompass informal as well as criminal activities*, no matter whether they produce value added or are just a transfer of funds or store of value, just as Feige (1979) proposed. The

underground economy therefore encompasses tax avoidance, criminal activities, informal activities (*i.e.* helping the neighbours) and omissions in a statistical sense.

As a result of this confusion in definitions and measurements, relatively few economists and econometricians have engaged in a field which by definition is doomed to be criticized for a lack of reliable information and data. Nevertheless, some courageous did; notable being the works of Gutmann (1977), Feige (1979 and 1990), Tanzi (1983), Schneider and Enste (2000), Lyssiotou, Pashardes and Stengos (2004), Ahumada, Alvaredo and Canavese (2007) and Alm and Emabye (2013) have to be mentioned. Their works are the scaffolds of today's rough estimates of the underground economy.

Although the relationship between the estimation of the underground economy and the estimation of the volume of money laundered lies primarily with the methods used, the overlap between the two measurements is growing. Money laundering requires a crime to be committed, for the proceeds thereof to be laundered.[17] However, not all crimes require laundering of proceeds, and some underground activities may actually not constitute a predicate offence for money laundering (*e.g.* helping neighbours) or may not be financially lucrative (*e.g.* homicide, terrorism). Moreover, the legitimate return on investment from money laundering may also need to be accrued to the volume of money laundered (Tanzi, 1997, p.93). The 4th EU Directive on Anti-Money Laundering however, explicitly includes tax crimes (albeit there is no unified understanding of what tax crimes constitute across the EU Member States) in the list of predicate crimes for money laundering.[18] Such legal development will certainly enlarge the scope of overlap between the underground economy and money laundering as tax crimes are reported to be highly financially lucrative (Internal Revenue Service (IRS), 2006) and will therefore become money laundered.

2.2. Methods to estimate the underground economy and money laundering

There are in principle five classical methods to measure the underground economy. Each method has its own empirical difficulties (Feige, 1990, p.993). The first is called *the direct method*. By means of surveys, the tax authorities try to find out how much tax income is unreported. This, usually, captures non-criminal activities and is biased as respondents have no incentive to report truthfully, even when randomized response techniques are used to protect the identity of the survey takers (*cf*. Böckenholt, Barlas & van der Heijden, 2009).

The second method measures the underground economy by statistical discrepancies such as the difference in *accounted incomes and expenses*. If the latter is greater, then the difference must consist of undeclared income constituting a means obtained through the underground economy. This type of measurement has become less popular. Thomas (1992) argued that

[17] *Ibid* 2.

[18] Article 3.4.f of the *"Proposal for a Directive of the European Parliament and of the Council on the prevention of the use of the financial system for the purpose of money laundering and terrorist financing"*, 2013/0025 COD, downloadable at http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52013PC0045

inconsistencies in measurements, such as statistics or measurement errors, casted serious doubts on this method (*cf*. Rossini & Thomas, 1990).

The third method dates back to the 1990s and uses labour or specific forms of capital as a proxy for the size of the underground economy. It assumes that changes in the labour force over time can efficiently proxy changes in the underground economy. The weakness of this accounting method, as stated by Schneider and Enste (2002), is that it does not allow for changes in the labour force that are inherent and independent from the underground sector. Therefore, an ageing population might reflect a lower share of workers to total population without implying a proportional increase of the labour working in the underground economy. In addition, illegal migrants and other social groups not working in the legitimate sector might have a significant impact on the measurements. The proxy variable approach developed by Kaufmann and Kaliberda (1996) and Lacko (1996) considers electricity input to be the main indicator of the underground economy. Excess electricity usage is assumed to signal illegal production in the underground economy. The criticism Schneider and Enste (2002) presented to the latter models is that they can neither account for exogenous changes in capital input use, nor can they capture the underground economy that does not make use of these factors of production. The critics further argue that indexing countries according to electricity/GDP and using an estimation of the underground economy in one base country to compute the underground economies of the other countries in the sample assumes away possibly vital country and culture specific characteristics. Using statistical discrepancies and proxy variables, though heavily criticized, are by now established, if not to say old fashioned ways of measuring the underground economy.

The fourth method to estimate the underground economy is known as *the CDA*. In 1980, Tanzi constructed an estimate of the money demand, using the monetarist approach as developed by Feige (1979) and Gutmann (1977). This approach relies on the Fisher equation (Fisher, 2006) and assumes that money is mainly used for transactions of the real economy. Using yearly data from 1929 to 1980, Tanzi (1983) suggested that the overall excess supply of currency was unrecorded cash money used in the underground economy. He then argued that the reasons for going underground and holding more cash were high taxes. Accordingly, for Tanzi, tax evasion was the crucial driver of the cash based underground economy.

Focusing thus on tax evasion, Tanzi (1983) built a linear logarithmic model where the cash to money supply ratio *(C/M_2)* was influenced by the personal income tax rates *(T),* the amount of cash wages to national income *(WS/NI),* the annual interest rates *(R)* and income per capita *(Y)*. The regression he used is presented hereunder.

$$\ln\left(\frac{C}{M_2}\right) = \beta_0 + \beta_1 \ln(T) + \beta_2 \ln\left(\frac{WS}{NI}\right) + \beta_3 \ln(R) + \beta_4 \ln(Y) + \mu \qquad (1.1)$$

Tanzi (1983) used Equation (1.1) to estimate the relation between taxes and cash to money supply. He then chose a base year where he assumed there was no underground economy and used the estimated coefficient for tax rates and the actual development of tax rates to estimate how much cash was used in the underground economy. Finally, the amount of non-disclosed transactions (*i.e.* the size of the underground economy) can be calculated by using the Fisher equation, where Tanzi (1983) assumed the velocity of "black money" to be similar to that of legitimate funds. Naturally, this estimation method is only possible when the coefficient for tax rates is found to be significant and positive, a crucial feature thus of this model.

Tanzi's CDA has fascinated many researchers, who worked on criticizing, modifying and testing his findings. Just as Tanzi (1983), Bajada's (1999, 2001 and 2002) interest in the underground economy of Australia was triggered by the unusually large supply of cash Australian dollars per capita. Bajada argued that the demand for currency is influenced by the income tax rate and by welfare benefits, directly and indirectly through the real disposable income. Breusch (2005b, pp.7-10), however, shows that the aforementioned works of Bajada are unsound as they are sensitive to the change of the units of measurement of the explanatory variables. When correcting for this sensitivity, the relationship of interest becomes insignificant. This chapter also acknowledges the efforts of Shima (2005) and Carolina and Pau (2007) who explored the explanatory power of the tax complexity, of the labour market regulations and of welfare benefits value on the cash based shadow economy. Subsequently, applying Tanzi's CDA on a large panel of countries, Alm and Emabye (2013) showed that high tax rates and weak enforcement capabilities induce higher cash based shadow economies. And, while they do not account for event analysis, Alm and Emabye (2013) acknowledged that in OECD countries, taxes are less able to explain the cash-based shadow economy.

Finally, the fifth method to measuring the underground economy makes use of latent variable models and is most popular among academics and politicians, especially due to its use in measuring the underground economy for almost all countries and jurisdictions of the world. The latent variable approach used by Schneider and Enste (2000) is referred to as the *DYMIMIC* (Dynamic Multiple Indicator Multiple Causes) model. This method links changes in observable causes with changes of observable effects (or indicators) of the underground economy in order to infer the movements of the intermediate latent value: the unobserved changes of the size of the underground economy (Schneider & Enste, 2000; Dell'Anno & Schneider, 2003; and Schneider, Buehn & Montenegro, 2010). Although seemingly more refined than earlier approaches, this method is heavily criticized by Breuch (2005b) who argued that it is vague in its specification, sensitive to the units of measurement and hard to reproduce. Breuch (2005b) also argued that the DYMIMIC model relies too much on the public's interest in large estimations. Despite all this criticism, one may consider the DYMIMIC

model as a step further in measuring the underground economy by using econometrics and economic reasoning. However, the DYMIMIC model measures only the change in the size of the underground economy and not the actual size of the underground economy. This means that estimations from another source are needed for the base year. Here the DYMIMIC model relies upon – guess: the CDA of Tanzi (1983).

Measurements of the amounts of money laundered, although less numerous, have developed in the same circumstanced mentioned earlier. Walker and Unger (2009, pp.826-827) argued that early efforts were made through case studies by criminologists, but case studies were soon recognized as insufficient tools as one could not assess how representative the sample analyzed was and to what extent focusing on these cases would not lead to a tunnel vision. A second method to estimate the volume of money laundered is based on surveys, but here, the disadvantage is the disincentive to truthfully fill in the surveys (*cf.* Levi & Reuter, 2006). Finally, the third and most popular method to estimate the volume of money laundered employs econometric techniques, which are subject to less rigid assumptions and therefore better able to generate accurate estimates. While many of the econometric models used to estimate the volume of money laundered are based on a modified gravity model (*i.e.* Walker & Unger, 2009; Ferwerda, 2012), many others rely on measurements of the underground economy (*i.e.* Chong & Lopez-de-Silanes, 2007; Argentiero *et al.*, 2008; Ardizzi *et al.*, 2013; Buehn & Schneider, 2013) (*cf.* Levi & Reuter, 2006). In conclusion, years after the CDA was first constructed, despite all the efforts to develop better economic and econometric models, progress in measuring the underground economy, and perhaps also the volume of money laundered, still relies crucially upon its validity.

3. Criticisms of Tanzi's method

3.1. Early criticism

The CDA has not been spared criticism. Tanzi's (1983) paper was criticized by, among others, Schneider and Enste (2002), Breusch (2004, 2005a) and Ahumada *et al.* (2007). Addressing the first step of Tanzi's model, Schneider and Enste (2002) argued that there is more to tax evasion than the size of tax rates. Their argued that tax morality and trust in the government are also important factors that Tanzi does not take into account. And finally, they argued Tanzi did not account for the usage of the US Dollar as international currency, as well as for an exogenous decreasing demand for deposits, both factors that could increase the demand for US currency next to tax evasion.

Addressing the second step of Tanzi's model, Schneider and Enste (2002) argued that Tanzi assumed a base year for which there was no underground economy without enlisting reasonable grounds for doing so. Additionally, Breusch (2005a) discharged the applicability of

the Fisher equation to cash in the underground economy and Ahumada *et al.* (2007) discharged the assumption that the velocity of currency is the same in both the official and the unofficial economy. Finally, Breusch (2004) mentioned that Tanzi did not report a Dicky-Fuller check on stationarity.[19]

3.2. Our criticism: only big change matters

Tanzi made certain assumptions related to the behaviour of taxpaying individuals: *"Underground, or shadow, economic activities are likely to use cash to finance transactions because payments made in cash cannot be traced while payments made by check, […] are more easily traceable" (Tanzi, 2002).* Using the tax rate as explanatory variable in a linear model, Tanzi (1983) assumed that taxpaying individuals reacted to an increase in the tax rate by going 'underground'. Moreover, after correcting for stochastic processes, the CDA as introduced by Tanzi actually captures the effect of the change in an external stimulus - the tax rate – on the aggregate expressed demand for cash.

Psychological and behavioural economic studies (*Cf*. Simon, 1969; Thaler, 1985; Kahneman, 1991) show that the perception of a stimulus – which, in this case, is the change in the tax rate – depends on the environment that surrounds the perceiving agents[20] – in this case, the taxpayers. Often used in behavioural psychology and in the management literature, the Weber-Fechner law combines two laws of human perception. The first is called Weber's law and states that people are more likely to remark change the bigger the change is (Ross & Murray, 1996). The second is called Fechner's law and states that subjective perception of change is proportional to the logarithm of the stimulus intensity – or, in other words, that small change is not subjectively perceived and that small intensity stimuli will leave subjects indifferent (Heidelberger, 2004). This indifference zone surrounding the stimulus is also known as 'the Weber fraction' (*Cf*. Thurstone, 1994).

Although not used in the field of tax evasion, the Weber fraction is often used in marketing literature to explain why small changes in prices are not decisive in changing buyers' purchasing decisions. The size of the indifference thresholds has been estimated for several types of goods (Bucklin & Gupta, 1999; Pauwels, Srinivasan & Franses, 2007), at different magnitudes (Grewal & Marmonstein, 1994) and in various price settings (Raman & Bass, 1988; Kalyanaram & Little, 1989; Monroe, 1990). In general, there is not one single Weber fraction – below which price changes do not change buyers' decisions – and moreover indifference thresholds vary in perceived gains and losses. Sirvanci (2011), for instance, found that, in the case of low-cost groceries, only price increases higher than 21% of the cost of the product led

[19] A check for Stationarity is needed in time series analysis as both the dependent and the independent variables may share a time trend, determined outside the model (Kendall & Ord, 1990). A model that has a unit root problem reports a high R-squared without having any real explanatory power.

[20] Throughout this PhD thesis, I use the economic concept of 'agent' – an actor whose decisions and actions are based on solving a simple or complex, well or ill-defined optimization problem.

to a significant change in the behaviour of the average buyer. Marques and Dehaene (2004) found that for frequent purchases, the Weber fraction was lower than for rare purchases. They also found that after a currency change, price intuition faces Weber fractions higher than 40%. And alternatively, Chang and Chiou (2007) found that the just noticeable difference in prices for their sample was a 15% increase. Finally, Grewal and Marmonstein (1994) showed that the time the consumers spent on trying to strike a bargain negatively related to the magnitude of the original price.

Building on this literature, this chapter explores a potential new criticism to Tanzi's method, one that focuses on its theoretical microeconomic foundations. The hypothesis tested in this chapter was that, tax payers go underground only in reaction to a tax change that overcomes their Weber fraction. The difficulty associated to testing this hypothesis related to the availability of only aggregate data. We therefore did not aim to find the exact Weber fraction, and assume that the margins of error to such a fraction are large. Nevertheless, we hypothesize that when taxes do not increase significantly, taxes play no role in explaining the cash driven underground economy. Conversely, we expected that a large increase in taxes would increase the cash based underground economy.

In order to test this hypothesis, we replicated Tanzi's model on Eurozone data. The Eurozone sample was characterized by stable taxes and furthermore, allowed us to address many of the earlier expressed criticism on Tanzi's method. Subsequently, we extended the sample of Tanzi until 2006 and reran his analysis thereon, while addressing some of the earlier expressed criticism. And finally, we reviewed the seemingly contradictory empirical literature on the CDA and analyzed the size of the tax changes captured by each of these papers.

4. Data

Tanzi (1983, pp. 290-291) collected yearly US data from 1930 to 1980 on the ratio of US currency holdings as a percentage of the monetary basis M_2, on real per capita income, on annual interest rates, on time and saving deposits, on the ratio of wages and salaries paid in cash to the national income, on the ratio of total income tax payments after credit to adjusted income and on the weighted average tax rate on interest income. We extend the database of Tanzi until 2006 by collecting data from 1975 – 2006. We used an overlapping 5 year period from 1975 to 1980, to avoid structural breaks due to new datasets (Table A1.5).

Tanzi revealed the large volatility of the ratio cash currency to deposits in the US over the period 1930-1980 thereby motivating why a fixed ratio (as assumed by his predecessors – Gutmann (1977) and Feige (1979)) is no reasonable assumption. Figure 1.1 graphs the evolution of US currency holdings as percentage of the monetary base M_2 while Figure 1.2 graphs the evolution of the ratio of total income tax payments after credit to adjusted income

in the US. Both figures include the extensions to Tanzi's original dataset (Table A1.3). The figures show that the volatility of the ratio cash to M_2 and of personal income taxes remained high after the 1980s.

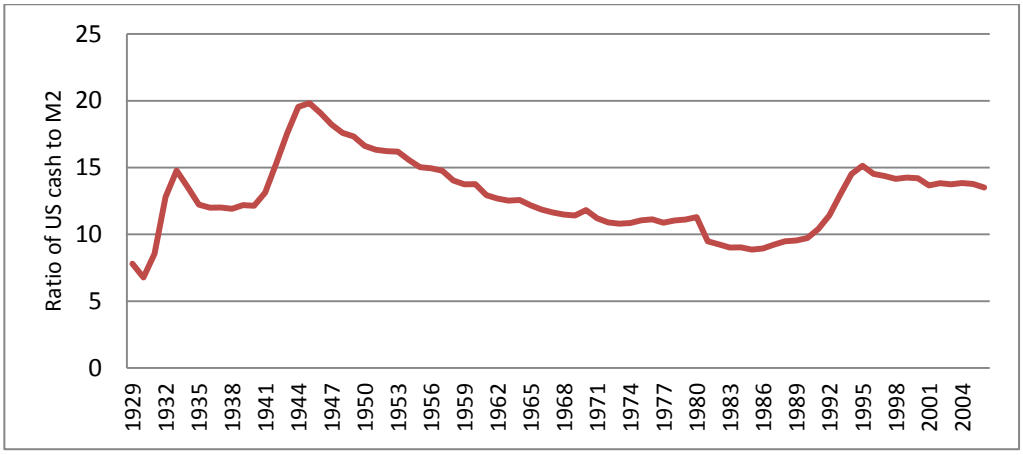

Figure 1.1: Yearly US cash holdings as percentage of the M2 monetary base. Adapted from Tanzi (1983) and updated until 2006.

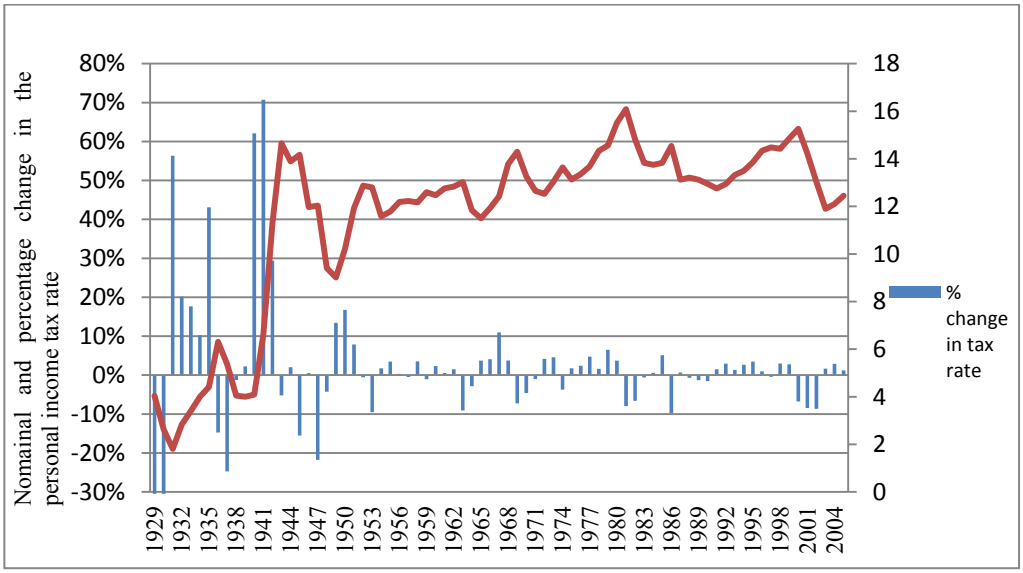

Figure 1.2: US personal income tax rate and fluctuations in the US personal income tax rate. Adapted from Tanzi (1983) and updated until 2006. The percentage change in the personal income tax rate is measured on the left-hand side scale. The nominal personal income tax rate is measured on the right-hand side scale.

Eurozone data is more scarce. Some variables are reported on a yearly basis while others on a monthly basis. Given the limited time period we used, we conducted the analysis on a quarterly basis. Keeping a stable distribution we used linear interpolation to create intermediate estimates for the yearly observations, while aggregating the monthly data by quarter (Table A1.4). We considered this fix to be highly lucrative. Furthermore, although data on, among others, taxes and GDP are reported per country, we could not use panel data, as the data on Money Supply are only reported at a European level. Instead, we used time series analysis on quarterly data of population weighted averages of Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia and Spain from 2002Q1 to 2008Q4.

The European Central Bank (ECB) provides monthly data of currency stocks it has in circulation, within and outside the Eurozone. We excluded cash reserves held by the central governments, assuming they have no bearing on the underground transactions in the European Union. Figure 1.3 plots the evolution of the ratio of cash to the money supply M_3, and shows that the amount of cash in the Eurozone has increased slightly since the introduction of the Euro. Data on Wages and Salaries, collected by Eurostat, reflects the development of total cash and in-kind remuneration of persons enlisted on a payroll. We used this as approximation of the semi-underground economy, which includes home workers, people with irregular income, regular payments or on the job payments (payments that do not depend on the working time but on the final output). Eurostat also publishes data on money market monthly interest rates and on income per capita per EU Member State.

We also made use of the tax measurements reported as a percentage of GDP and as a percentage of total tax collected in The European Commission Taxation and Customs Union Report of 2009. Contrary to the case of the US, the European tax rates are very stable, with quarterly changes of less than 1% (Fig. 1.4).

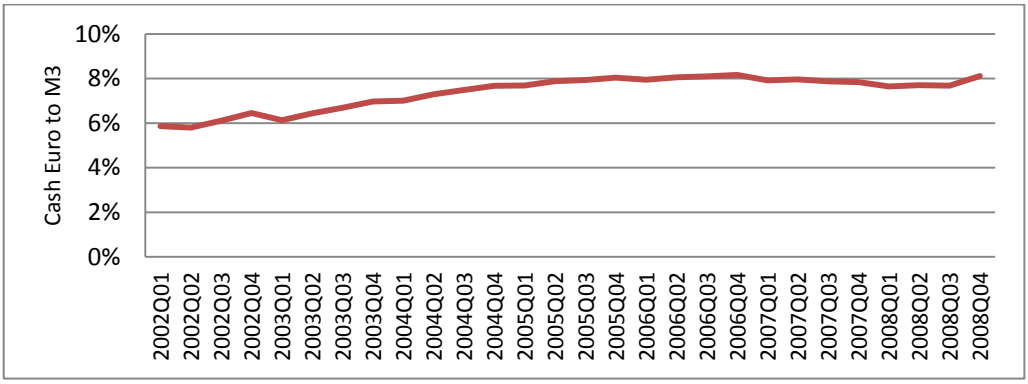

Figure 1.3: Quarterly estimates for the Eurozone cash holdings as percentage of M3 holdings.

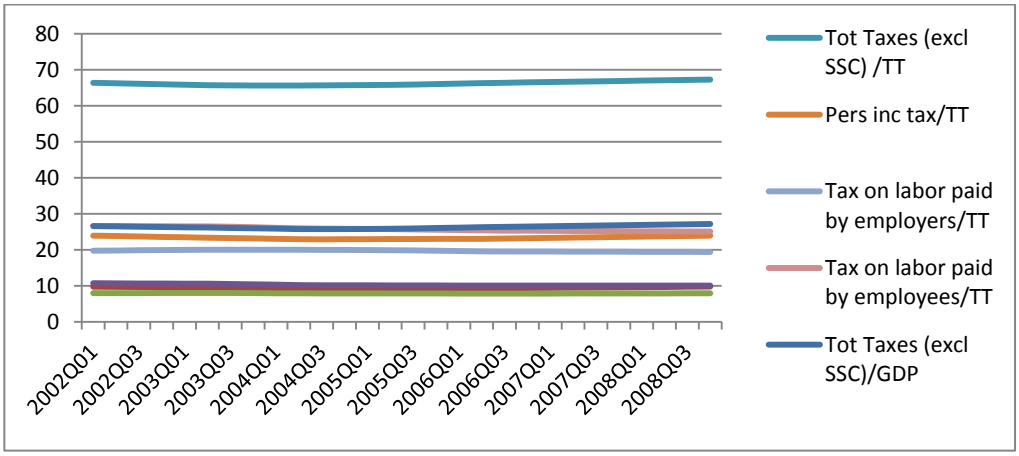

Figure 1.4: Quarterly fluctuations of the tax rate in the Eurozone – expressed as Total Taxes collected excluding Social Security Contributions per Total Taxes collected and per GDP; Personal income tax collected per Total Taxes collected and per GDP; Collected tax on labour paid by employers per Total Taxes collected and per GDP; and Collected tax on labour paid by employees per Total Taxes collected and per GDP.

5. Results

5.1. Applying Tanzi's method to the Eurozone dataset

We applied the model of Tanzi (1983) to the Eurozone, and addressed most of the early criticism. In Europe, 2002 offered the unique chance of studying an economy without an underground economy in Euros. It was not possible at that time to fuel the underground economy by means of Euro cash and coins, as the old currency – if illegal – could not have been transformed into Euros yet.[21] In this case thus, the choice of the base year is not arbitrary, but the result of a natural experiment that took place in the European Union. We replicated the model of Tanzi using the following specification:

$$\ln\left(\frac{M_1}{M_3}\right)_t = \beta_0 + \beta_1 \ln(1+T_n)_t + \beta_2 \ln\left(\frac{WS}{Y}\right)_t + \beta_3 lnR_t + \beta_4 \ln\left(\frac{Y}{N}\right)_t + \mu_t \qquad (1.2)$$

The cash to money supply ratio *(M_1/M_3)* depended on different tax rates *(T_n),* the amount of income received in cash to personal income *(WS/Y),* interest rates *(R)* and income per capita *(Y/N).* We analyzed several taxes that could affect the decision to go underground in a similar way to personal income taxes – *i.e.* total taxes excluding social security contributions, taxes

[21] In some European countries, parallel currency use was possible for a couple of months, but we assumed this to be of minor importance.

on labour paid by employees, taxes on labour paid by employers.[22] Finally, given the increasing expansion of non-cash transactions and services, which corroborated with a period of non-violent economic development, it was unreasonable to assume that the demand for deposits has significantly lowered if at all, between 2002 and 2008 in the Eurozone. This suggested that a *growing demand for Euros in cash was not motivated by a decrease in consumers' willingness to hold bank deposits.* We were, nevertheless, not able to capture Torgler and Schneider's (2009) *"moral obligation to pay taxes"*.

The results of the pooled OLS regression are showed in Table A1.1. As such, the model suffers from autocorrelation and unit-root, according to the Durbin Watson and the Dicky Fuller tests. The first difference pooled OLS estimations depicted in Table A1.2 show that taxes are incorrectly signed and not significant. Tanzi's model therefore, performed poorly on the Eurozone data, once we corrected for all earlier expressed criticism (Table 1.1). This could be due to the limited number of observations, due to the fact that EU citizens do not hold extra Euros in cash in response to slight tax increases, due to the fact that people in general do not hold extra Euros in cash in response to slight tax increases or due to the fact that taxes do not play a role in explaining the extra cash demand altogether.

5.2. *Applying Tanzi's method to an enlarged US dataset*

Addressing the limited size of our sample, we extended the US dataset of Tanzi until 2006, and replicated his analysis on the enlarged database. The Dickey Fuller test (Dickey & Fuller, 1979) revealed that in the original data used by Tanzi (1983), as well as in the extended dataset, the (C/M_2), (T) and (Y) variables suffered of a unit root problem. We then, therefore, corrected for a stochastic process and estimated Equation 1.3.

$$\Delta ln\left(\frac{C}{M_2}\right) = \beta_0 + \beta_1 \Delta\, ln(T) + \beta_2 \Delta\, ln\left(\frac{WS}{NI}\right) + \beta_3 \Delta ln(R) + \beta_4 \Delta ln(Y) + \mu \qquad (1.3)$$

Interestingly, as Table 1.1 shows, Tanzi's intuition was not spuriously driven. After correcting for the unit root, taxes retained a significant influence on the cash based underground economy. Moreover, the model kept a high explanatory power. Finally, also when we expanded the dataset of Tanzi until 2006 the relationship held, albeit the lower explanatory power.

[22] Bajada (1999, p. 373) argued that average taxes could be used as substitute for personal income taxes as they too could proxy the trigger for people to go in the underground economy. Alm and Emabye (2013) also made use of the ratio of total taxes to GDP, given the data limitations encountered in setting-up a panel dataset.

Table 1.1: Applying Tanzi's (1983) CDA to the original US data, to the extended US data, and to the Eurozone data – regression design, size and significance of the income tax coefficient, explanatory power and presence of a unit root.

Sample	*Regression*	*Income tax coeff.*	*Adj-R^2*	*Unit root*
Eurozone; '02-'09	$\Delta\ln\left(\frac{M_1}{M_3}\right)_t = \beta_0 + \beta_1\Delta\ln(1+T_n)_t + \beta_2\Delta\ln\left(\frac{WS}{Y}\right)_t + \beta_3\Delta lnR_t + \beta_4\,\Delta\ln\left(\frac{Y}{N}\right)_t + \mu_t$	*0.24*	*0.59*	*No*
US;'29-'80	$ln\left(\frac{C}{M_2}\right) = \beta_0 + \beta_1\,ln(T) + \beta_2\,ln\left(\frac{WS}{NI}\right) + \beta_3 ln(R) + \beta_4 ln(Y) + \mu$	*0.36***	*0.89*	*Yes*
US;'29-'80	$\Delta ln\left(\frac{C}{M_2}\right) = \beta_0 + \beta_1\Delta\,ln(T) + \beta_2\Delta\,ln\left(\frac{WS}{NI}\right) + \beta_3\Delta ln(R) + \beta_4\Delta ln(Y) + \mu$	*0.32***	*0.54*	*No*
US;'29-'06	$\Delta ln\left(\frac{C}{M_2}\right) = \beta_0 + \beta_1\Delta\,ln(T) + \beta_2\Delta\,ln\left(\frac{WS}{NI}\right) + \beta_3\Delta ln(R) + \beta_4\Delta ln(Y) + \mu$	*0.22***	*0.42*	*No*

Note. **p < .05

We further explored the causal relationship between taxes and the extra cash demand in the US, using rolling regressions. Figure 1.5 presents the dynamics of the β coefficient of the tax ratio on the cash surplus for 57 consecutive periods of 30 years. We employed Tanzi's (1983) original regression after correcting for unit root, as shown in Equation 3. Figure 1.5 shows that a significant causal relationship could be identified in the first periods, while the β coefficient for the effect of taxes on the money supply did not significantly differ from zero for most of the rest of the sample originally used by Tanzi (1983). Only the first time range between 1930 and 1960, confirmed the relationship between taxes and excess demand for cash money. Although the coefficient did increase in the latter period, it was no longer a significant relationship.

Figure 1.2 shows that although personal income taxes in the US have almost constantly increased over the time sample, in the last decades they have increased by little. In fact, just as in Europe, the last decades saw a stabilization of personal income taxes in the US. Furthermore, between 1932 and 1945 the ratio of total income tax payments after credit to adjusted income rose from close to 2% to almost 15%, an increase of more than 700%. It is at the same time that the ratio of cash to deposits spiked, as Figure 1.1 shows, and that Tanzi's relationship held. After World War II, the ratio of total income tax payments to adjusted income in the US seldom increased by more than 5% on a yearly basis. Even milder, European taxes did not increase by more than 1% on a yearly basis (Fig. 1.4). And as Table 1.1 shows, on the extended US dataset as well as on the European dataset, Tanzi's model had no explanatory power.

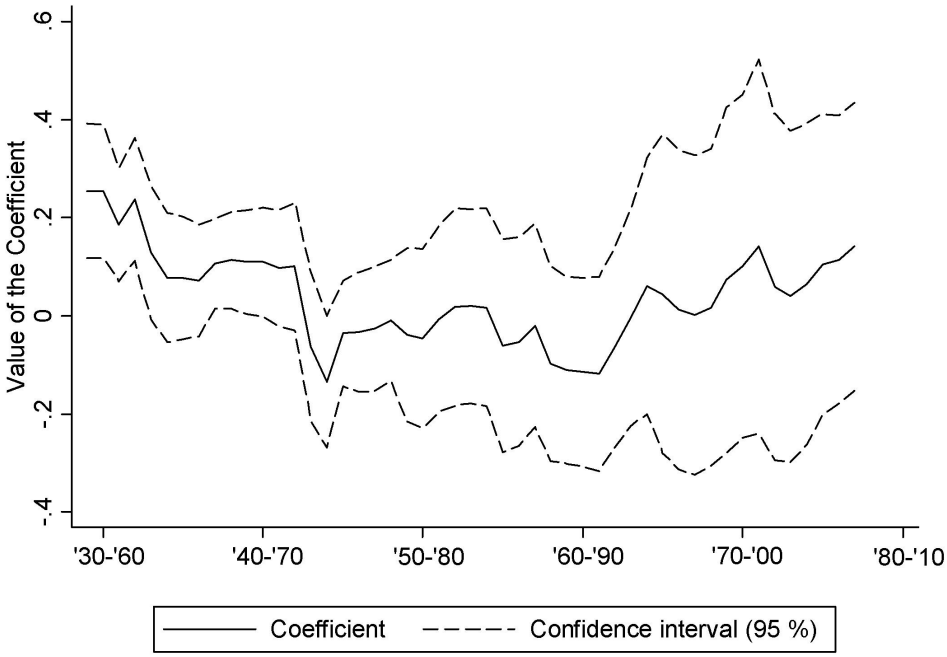

Figure 1.5: Moving Tax Coefficient for 57 Consecutive 30-year Sub-samples. The solid line shows how the coefficient of tax develops over time with 30 year periods (the first observation is 1929-1959, the next observation is the period 1930-1960 etc.), the dashed lines above and below the coefficient line show the confidence interval of the coefficient on a 5% significance level. When zero lies within the confidence interval (happening for the first time in the period of 1933-1963) the coefficient is not significantly different from zero at the 5% significance level.

Immense changes took place in the United States in the early 1930 recession. Before the Great Depression US companies were producing at overcapacity and exporting hugely. The US balance of payments implied a strong currency that could not efficiently compete in exports; the domestic market was left to accommodate for non-exported surpluses; the government did not contribute to absorb supply, companies were closed hence unemployment rose, banks' balance sheets contracted and the situation spiralled out of control (Eichengreen, 1992). Moreover, major capital outflows combined with the soaring unemployment caused by the dismissal of national industries may have had an impact on the view people took towards taxes. When discussing the approach of Feige (1979), Tanzi (1980) also mentioned government's perceived reliability to be one factor non-accounted for, but with a significant toll on the size of the underground economy. In the face of significant financial hardship to which the government was not seen to actively contribute to ameliorate, people were

assumed to have lost faith in the government and sought to avoid paying taxes. Whether it was a lack of trust in government, or a means to reduce financial hardship, souring taxes did reflect in the extra demand for cash (Tanzi, 1980). And, as taxes stabilized, smaller tax changes no longer reflected in the extra demand for US dollars.

This argument is in line with the psychophysics literature where changes below a certain Weber fraction are not be observed cognitively and do not thereby trigger reaction. Small tax increases would, therefore, not directly trigger proportional increases of the tax based underground economy. Finally, we reviewed the literature that applies Tanzi's CDA, to see whether this finding was confined to the US and the Eurozone only and to explore the size of the Weber fraction for tax evasion.

5.3. Additional literature estimating the underground economy via the Tanzi's method

Studies that have attempted to measure Weber's fraction when prices increase estimated it to range from 17% to 40% of the original price (*Cf*. Marques & Dehaene, 2004; Chiang & Chiou, 2007; Sirvanci, 2011). Table 1.2 shows that research that successfully applied Tanzi's CDA also employed time samples which contain at least one large tax fluctuation. Table 1.2 shows that time samples where yearly tax increases were smaller than 14% did not support a tax-cash holding relationship as Tanzi suggests. These tax changes fall within the Weber fraction and, as such, do not trigger changes in the aggregate cash holdings.

Finally, Table 1.2 illustrates how effective the government is perceived by its citizens, in every country where Tanzi's model has been tested. Unfortunately the Worldwide Governance Indicators do not go back in time further than 1996 and therefore actually do not capture trust in governments in the period on which Tanzi's assumptions were tested in both Australia and the US. Nevertheless, US Pew Research Centre (2014) reported a constant decrease in the level of trust US citizens had in their government over the period 1958-2014. Conversely, Table 1.2 shows that perceived governmental effectiveness is not correlated with tax evasion via the excess demand for cash. The second column reports on whether Tanzi's intuition is found to hold on the given sample, either in its original form or with specific adjustments.

Table 1.2: Academic works that applied Tanzi's CDA on US, Australian, Turkish, Nigerian and Guyanese data.

Paper	Tanzi specification works in author's view	Country (WGGI rank)[a]	Time period	Max yearly % change in taxes
Tanzi (1983)		US (92)	1929-1980	70%
Bajada (1999)	Yes (with adjustments)	Australia (94)	1967-1996	53%
Ogunc and Yilmaz (2000)	No (Ogunc and Yilmaz, 2000: 23)	Turkey (61)	1965-1998	14%
Ariyo and Bekoe (2012)	Yes (with adjustments)	Nigeria (15)	1975-2009	31%
Faal (2003)	Yes (with adjustments)	Guyana (49)	1970-2000	40%

Notes. Adapted from Tanzi (1983), The Australian Bureau of Statistics, The Economics Web Institute, The World Bank and Faal (2003); [a] We took the average ranking the country had from 1996-2013 in the Worldwide Governance Indicator: Government Effectiveness (http://info.worldbank.org/governance/wgi/index.aspx#reports)

Table 1.2 does not cover all the research employing Tanzi's method, since very few papers exposed their datasets, and since inconclusive results are usually always published/ publishable in the scientific community (*cf.* Rothstein, Sutton and Borenstein, 2005). In fact, with one exception, Table 1.2 refers to papers that could successfully replicate the findings of Tanzi. Moreover, table 1.2 also only discusses that subset of academic works applying Tanzi's method for which data was made available or could be found following the authors' instructions. Under these circumstances, Table 1.2 should not be regarded as a meta-analysis of the literature on the application of the CDA, although such endeavour may prove to be a valuable contribution to the literature.

6. Conclusion and policy recommendations

In this chapter we revisited the CDA to estimating the underground economy as developed by Tanzi (1983). His model conjectured that one of the factors that deterred individuals from legitimately transacting in the US was that they had to give away part of the transacted wealth in the form of taxes. He argued that the evolution of cash holdings in the US could be explained by the level of personal income taxes. Tanzi's work was often used in measuring the size of the underground economy even by his most vocal critics (*i.e.* Schneider & Enste, 2002; Bajada, 1999). Nevertheless, not all studies that used Tanzi's CDA were able to find evidence to this intuition (*i.e.* Ogunc & Yilmaz, 2000).

In this chapter we investigated the validity of Tanzi's method and focused particularly on the theoretical micro-economic foundations of the model. While Tanzi assumed a linear relationship between taxes and the cash based underground economy, our hypothesis was

that, in line with the psychophysics literature, tax payers go underground only in reaction to a tax increase that overcomes their Weber fraction. We tested this hypothesis by replicating Tanzi's model on the Eurozone dataset – a sample characterized by stable taxes, and found that taxes could not explain the demand for extra cash Euros. Secondly, we extended the dataset used by Tanzi (1983) until 2006, and replicated his analysis while correcting for unit root. We found that the relationship between taxes and the demand for cash US dollars only held between 1930 and 1960, when US personal income taxes varied from one year to the other, sometimes by as much as 70%. Additionally, in the subsequent decades, when personal income taxes stabilized, we found no significant influence of the change in tax on the extra demand for cash US dollars. Finally, we reviewed a sample of seemingly contradictory empirical literature on the CDA and we measured the size of the tax changes captured in each of these papers. In line with the law of diminishing sensitivity to sensory stimuli, we found that only large tax changes drove the excess demand for cash.

The finding that the relationship between taxes and the extra cash demand only holds in times of high tax volatility is of utter importance, given the role of Tanzi's method in the exploration of the underground economy. Seeing how a confirmatory analysis is hard to foresee in the context of measuring the underground economy, having a good intuition about the mechanisms that constitute the micro-foundations of Tanzi's model is therefore imperative. The choice of sample is highly important for the accuracy of the estimates of the underground economy, as the replication of Tanzi's method in the US shows. Finally, applying Tanzi's method to a dataset in which taxes are relatively stable is likely to yield insignificant coefficients. Using an insignificant regression coefficient to calculate the excess demand for cash, captures some error term and leads to misleading estimations of the underground economy. Consequently, Tanzi's method should only be applied in times of dramatic tax changes, if used effectively.

As such, our findings contribute to the increasing volume of research dedicated to estimating the underground economy and support two important arguments of the literature on the underground economy. First of all, we need to unify the different definitions of what is being measured in the underground economy, such that the estimates can be compared in a meaningful way. And secondly, as Tanzi (1999) pointed out when evaluating the efforts undertaken following his seminal paper, that the academic society needs a more rigorous review process for the methods and the proxies used in measuring the underground economy (and indirectly the volume of money laundered), as without them, the question of what is actually being measured and explained may remain unanswered.

More generally, this chapter highlights the challenge of identifying shared features of studies attempting to measure the underground economy, especially when only the significant results are published. A clear recommendation is that researchers provide, in their publications, the

original datasets used and otherwise refer clearly to their sources and to the eventual transformations data undertook. This is especially relevant when data were manually collected and when the national statistical infrastructures are not optimized for English speaking researchers. In line with this argument, we recommend that evaluations of the underground economy be replicated as any other event study as to allow for a better understanding of the nature of the events driving the estimations.

Chapter 2 – Effective information sharing: the undervalued component of the Anti-Money Laundering fight

1. Introduction

The first Anti-money laundering (AML) legislation was born in 1986 in the US.[23] In 1989 the Financial Action Task Force (FATF) was founded by the G-7 in order to set international standards and thereby coordinate the global effort to combat money laundering. These global efforts were motivated by widespread concerns on the scale and scope of organized crime – at first on drug trafficking and later, on fraud and tax evasion – and by the intrinsic belief of norm setters that these solutions are also effective (Stessens, 2001). In the meantime however, several researchers (Stessens, 2001; Ross and Hannan, 2007; Takáts, 2007; Gelemerova, 2008; Dalla Pellegrina and Masciandaro, 2009; Unger & van Waarden, 2009) have started inquiring into the real effectiveness of the AML policies. When convictions rates are seen as indicators of effective AML policies (*cf*. Unger & Van Waarden, 2009), why is the number of convictions for money laundering in general, so low and so different across countries? This chapter argues that defective communication[24] may partially explain the difference in convictions across Europe and suggests that improving communication among law enforcement agencies will improve the repression of money laundering.

Economists regard money laundering as a mean to increase the information asymmetry between law enforcement agencies and criminals (*cf*. Masciandaro, 2007). Consequently, the thought paradigm of law enforcement representatives is that, in order to obtain advantages over money launderers, it is imperative to posses the most up-to-date accurate information regarding their intentions and capabilities (United Nations Office on Drugs and Crime (UNODC), 2010, p.2). Acknowledging that without relevant information convictions cannot be secured, the FATF, therefore, started ensuring that this information is collected. Accordingly, in 1990 the FATF issued the so called forty (and later forty nine) Recommendations,[25] in which, it obliged entities such as banks, (and later added) dealers of large values, notaries, lawyers to

[23] Money Laundering Control Act of 1986, Pub. L. No. 99-570.

[24] For the purpose of this chapter, effective communication among law enforcement agencies is seen as effective information sharing among law enforcement.

[25] FATF recommendations were modified in 1996, 2003, 2004 and 2012. All texts can be downloaded at www.fatf-gafi.org/topics/fatfrecommendations/documents/internationalstandardsoncombatingmoneylaunderingandthefinancingofterrorismproliferation-thefatfrecommendations.html

report their suspicions of money laundering[26] to a newly established entity in their country – the Financial Intelligence Unit (FIU). The FIU has to collect, filter the relevant information and pass it onto the relevant law enforcement agencies, which, in turn, have to filter the relevant information and build a case-file and present it to the courts. Finally, the courts can convict the defendant for money laundering on the basis of the information they receive (*cf*. Stessens, 2001).

Unger and Van Waarden (2009) argued that the legislators in the US and in Europe started by regulating precisely what should be reported by the obliged entities. Under the so called *'rule-based approach'*, all transactions above the thresholds imposed by the legislator had to be reported. This approach was short lived as. Although it clear, transparent and able to minimize the legal risks and uncertainty for businesses, it leads to high administrative costs and allows criminals to easily escape detection by transacting just below the threshold (Unger &Van Waarden, 2009, pp.956-957). Under the later introduced *'risk-based approach'*, reporting entities had to estimate the risk of a transaction themselves (Unger &Van Waarden, 2009). Unfortunately, Pieth and Aiolfi (2003), Takáts (2007) and Dalla Pellegrina and Masciandaro (2009) showed that this approach did not solve the 'information overload' problem. In fact, from fear of being punished, the obliged entities would still over report, and give little or no concern to how usefulness their information for law enforcement to sanction money launderers (*cf*. Takáts, 2007). In conclusion, under the rule-based approach, there was a feeling that the information gathered lacked value for law enforcement because (1) it was easy for criminals to avoid triggering suspicion, (2) massive volumes of information reached the FIU and (3) it was not clear to the law enforcement agencies what the value of the information they received was. While (1) and (2) were addressed with the risk-based approach, this chapter argues that less emphasis was placed on (3), which is, in effect, crucial.

In this chapter, I look at the way information sharing among law enforcement agencies in charge with the repression of money laundering can reduce the information asymmetry between them and money launderers, and can therefore increase the probability of punishment for detected criminals. Recognizing that information is a good with specific compositional and growth properties (*Cf*. Ahdieh, 2011), I have focused on the surprise value of information and on the maintenance of its value upon transmission. I have focused on these, with a view to effectively decrease the information asymmetry between money launderers and the law enforcement having the capacity and resources to repress, accordingly. My hypothesis is that countries where the information about money launderers is more effectively dispersed among law enforcement agencies are more effective at convicting money launderers. I used the theory of Shannon (1948) and constructed a measure of the

[26] Reports on the suspicion of money laundering are constructed very differently across the EU (*cf.* Ferwerda, Deleanu, van den Broek & Unger, 2013). For this purpose, I employ the term 'suspicion report' to denote reports received by the European FIUs, irrespective of design.

information sharing amplitude in the national AML information network. I was able to do so for all 27 EU Member States as I built on a set of information diagrams developed by ECOLEF (2013). Second, I amassed several measures of effective repression of money laundering, by merging the ECOLEF (2013) and the Eurostat (2013) databases. Finally, I used pair-wise correlations and regression analysis to show that countries sharing information better had significantly higher recordings of convictions for money laundering. This relationship held also when correcting for the different levels of money laundering threat countries were exposed to. Finally, I saw that liaison officers significantly reduced the institutional distances among the different law enforcement agencies involved in the efforts against money laundering.

Importantly, this chapter has shown that too little attention has been dedicated to the process of information sharing that takes places among law enforcement agencies, although this plays a significant role in securing the effectiveness of the AML policy. I believe that the reasons thereof are threefold. First of all, the guidelines of the FATF assume having communication mechanisms is sufficient to ensure that information does not lose value when communicated between different organizations (*cf*. FATF, 2003, p.11; FATF, 2009a, p.76). Secondly, country reports are not sufficiently developed on an abstract level to doubt this assumption, as they are, in fact, a check of cooperation in the books. Thirdly, researchers did not approach this question for two reasons. Comparative applied legal research usually accommodates at maximum a handful[27] of countries and statistical data gathered at the EU level on money laundering was, until recently, not sufficiently developed to conduct econometric analysis on (ECOLEF, 2013, pp.282-292).

This chapter unfolds with a literature overview. Section 3 discloses the model used to measure effective communication among national organizations involved in the fight against money laundering. Section 4 introduces the data and the methods to be used in the analysis. Section 5 presents the results and Section 6 concludes and makes several policy recommendations.

2. Literature overview

There is a need to understand what drives and what impedes AML efforts. The effectiveness of AML policies has, so far, been studied from an information technology perspective (*cf*. Gao *et al.,* 2006), from a doctrinal perspective (law in the books) (*cf*. Gelemerova, 2008; Stessens, 2001; Deloitte, 2010), from a law and economics perspective (*cf*. ECOLEF, 2013; Tak, 2005), as well as, from an economic perspective (*cf*. Unger & van Waarden, 2009). All these studies

[27] Research conducted on the differences in criminal justices systems in Europe done by Tak (2005), is one of the few to discuss practices in 25 EU Member States.

have focused on identifying various technical, legal and economic barriers that impede the European AML efforts.

The information technology literature, for instance, looked for the best artificial intelligence solutions for detecting money laundering. Smart solutions isolate the relevant suspicious transactions (*cf.* Kindgon, 2004) and create financial analyses of the individuals suspected of laundering money (*cf.* Gao and Xu, 2009). These suspicion trigger solutions are designed for several types of users: obliged entities (in particular for financial institutions), and financial analysts working within FIU, Police, Supervisory agencies and the Prosecution (see review of Watkins *et al.*, 2003). Yet no attention is paid, within this literature, to the way information is effectively shared and valorised, after suspicion has been triggered.

Focusing on the legal barriers, European Commission tasked Deloitte in 2010 to review the way the Third AML/CFT EU Directive[28] was implemented in the national legislation of the Member States. The report concluded that legal implementation of the Directive took place without major disruptions (Deloitte, 2011). So if, in effect, legal differences were not driving the effectiveness of the AML efforts, what did? In 2010, the EU Commission also mandated the University of Utrecht to conduct study on the effectiveness of the EU anti-money laundering and combating the financing of terrorism policies. The multidisciplinary analyses reveal, among others, that it is not so much differences "in the books" but differences "in practice" that explain efficiency: from the differences in reporting and supervision systems, to the various extra tasks assigned to the FIU, to the different interpretations that law enforcement agencies across Europe give to the money laundering definition (ECOLEF, 2013, pp.127-137). A complementary conclusion is reached by Eurostat. In a 2013 Working Paper, Eurostat acknowledged that for a cost – benefit analysis of the AML policies "more is required than a *"bookkeeping style" perspective on money laundering that runs from the filing of the suspicious transaction report to criminal conviction"* (Eurostat, 2013, p.11). So, if any meaningful analysis was to be made, more had to be known about what lies underneath the previously collected statistics on money laundering. Knowing what happens after information reaches one AML law enforcement organization becomes important for policy makers.

Approaching the problem from a legal and institutional perspective, Tak (2005) gave a compelling overview of how the Police, the Prosecution authorities and Ministries work towards crime prevention and crime deterrence in Europe. Tak (2005) showed that there were significant differences in the shapes and roles of these organizations and in the way they hierarchically interacted with each-other. These differences could, naturally, affect both the effectiveness of crime repression as well as the statistics on crime. Institutional differences

[28] Directive 2005/60/EC of the European Parliament and of the Council of 26 October 2005 on the prevention of the use of the financial system for the purpose of money laundering and terrorist financing [2005] OJ L309/15, downloadable at http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:32005L0060

that are relevant to the countering of money laundering were summarized by Kristen in ECOLEF (2013, pp.164-166). These were, among others, the allocation of the power to initiate prosecution, the type of prosecutorial specialization and the sharing of the criminal investigation task. As Kristen explained, the choice between the principle of legality and the expediency principle with respect to mandatory prosecution, may explain the differences in statistics on prosecutions for money laundering across Member States. Subsequently, depending on who can initiate prosecution – whether it is the public prosecutor only, or victims and other organizations, as well – there may be more or fewer AML prosecution started. Moreover, in terms of improving law enforcement efficiency, criminal cases should be allocated according to their difficulty to those prosecutors with the right financial crime expertise, and resources should be allocated among the law enforcement authorities in relation to the tasks they have, also with respect to the AML law (ECOLEF, 2013, pp.164-166).

Consequently, several legal, economic and institutional barriers to the effective repression of money laundering in Europe have been explored. The literature has, however, not dealt with the barrier of non-effective communication after suspicion has been triggered. The FATF dedicates little attention specifically to the way information is shared among law enforcement agencies and to the way this can be effectively quantified and managed. Recommendation 31 states *"Countries should ensure that policy makers, the FIU, law enforcement authorities, supervisors and other relevant competent authorities, at the policy-making and operational levels, <u>have effective mechanisms in place</u> which enable them to cooperate, and, where appropriate, coordinate domestically with each other concerning the development and implementation of policies and activities to combat money laundering […]"* (FATF, 2003, p.11). The FATF Methodology for Assessing Compliance only describes the concept of effective mechanism (FATF, 2009a, p.76) and therefore assumes that a communication channel suffices for the information not to get lost in communication.

3. Modelling effective communication

The assumption often used in the economics of money laundering is that criminals use laundering techniques to maintain opacity, whereas law enforcement agencies gather information on financial transaction and criminals in order to reduce this informational asymmetry (*Cf*. Masciandaro and Portolano, 2004; Masciandaro, 2007). Framing money laundering from an asymmetric point of view was appealing, as the solution to the problem then appeared intuitive: agencies involved in the AML fight should try to break the veil of ignorance that separates them from the money launderers. In this chapter, I argued that, since repression is hierarchically organized, the mere gathering of information is not sufficient. Instead, the information has to reach the organization with the capacity (*i.e.* resources, expertise etc.) and authority to punish accordingly. If this latter organization is not the one

that broke the veil of ignorance, the *effective communication of this information* is a necessary condition to effectively reduce this information asymmetry.

Network theory (*cf*. Jackson & Wolinsky, 1996) sheds light on the way proximity and being connected to our peers affects the degree to which we understand them and their behaviour. Goyal (2007) built on earlier mentioned work and showed that correctly anticipating what others thought, depended on how connected one was with them. Two entities that were connected were therefore better able to circulate ideas, and share information and were less surprised by each other. But similarities were good only to the extent that they allowed new knowledge to be generated.

In this chapter, I followed the work of Kostova (1997) on measuring institutional distance and applied it to the communication among the organizations with a role in the repression of money laundering. Initially applied in the macro-economic literature, I used it at a mezzo-level, for the purpose of simulating the connectivity of national law enforcement organizations. As such, institutional distance is a concept developed by the management literature that measures the differences between country specific sets of rules (Kostova, 1999). Particularly, Kostova argued that *there are three components to an institutional distance: a regulatory, a normative and a cognitive distance*. Regulatory distance refers to the difference in rules that promote and discourage certain behaviour (Kostova, 1997). Normative distance refers to the informal assumptions and beliefs about how society works and how humans behave (Kostova, 1997). Finally, cognitive distance is viewed by Kostova (1999, p.314) as the difference in *"the way people, notice, characterize and interpret stimuli from the environment".*

Subsequently, when addressing how institutional distance affects communication, I followed the seminal work of Shannon. In his paper "A mathematical theory of communication", Shannon (1948) argued that a message is transmitted from an information source with the help of communication symbols, which in turn are exchanged between the parties involved, through a communication channel. Shannon argued that the choice of the symbols for the purpose of compiling a coherent message can be seen a departure from a random process. The value of the message could thus be quantified by measuring this departure from randomness. Shannon thus, proposed a measure of the potential information contained in a message that equalled the probability that this message surprised, given that it was coherent and understood.

According to the International Monetary Fund (IMF) (2004) report, information about a possible money laundering offence enters the AML information flow through two main gates: the law enforcement and financial gates. On the one hand, law enforcement organizations have their sources that supply information over a wide array of crimes, inter alia money laundering and the corresponding predicate offences – *e.g.* other investigations, informants, under-cover actions, tip-offs. On the other hand, Gilmore (1999) and Schott (2006) argued

that the reporting entities held precious, first-hand information about their customers and were therefore best able to distinguish the unusual transactions that their clients might have performed. The reporting entities – a title that originally encompassed the classical financial institutions and that later grew to encompass casinos, brokerage, securities firms, notaries, lawyers, real estate agencies, auditors and more – were thus financial gateways for information and constituted the second main source of information. The development of these financial gateways has been supported by the FATF whose strategy transformed the obliged entities into watchmen of the market (*Cf*. Gelemerova, 2008). Furthermore, an FIU was established as national organization that collects these suspicions and passes what is relevant to the adequate law enforcement authorities (2005/60/EC Directive, Art. 21). As Stessens (2001) explained, suspicion reports (as well as other information relevant to money laundering cases) could be used in several instances: from detecting money laundering, to investigating a criminal case, to building a case file against a suspect; and finally, it could be used as evidence and proof in court. As Kristen explained in ECOLEF (2013, p.164), the information on suspicion provided by the FIU is cross-checked for confirmation and will eventually be compiled into a case file against the suspect. The prosecutor decides whether or not to prosecute, on the basis of the information contained in the dossier. So, in effect, the prosecutor's plea and consequently, the judgement of the court, depend on information effectively reaching them, after passing through many other law enforcement organizations (ECOLEF, 2013, p.164). Section 4 reports on how information flows among these organizations in the EU.

Let $d(i,j)$ measure the institutional distance between two organizations i,j involved in countering money laundering. I assumed that obliged entities can be grouped together from an institutional point of view. Similarly, I grouped together all other non-obliged agents that can report to the FIU upon suspicion of money laundering, under the heading *"Other financial gateway"*. The FIU can also receive information from all other FIUs to which it is connected. Similarly, the Police has its sources of information, grouped under the heading *"Criminal investigation gateway".* This grouping was needed to ensure parsimony and to ease comparison across the very diverse 27 EU Member States. In general, let m denote the number of groups of institutionally similar agencies with a role in countering money laundering. In this chapter,

$$m = card(\{'FIU','Police','PPO','Court'\} \cup \{'Other\ FIUs','REs','Other\ financial\ gateway','Criminal\ investigation\ gateway'\}) = 8.$$

Let

$$i,j \in \{'FIU','Police','PPO','Court'\} \cup \{'Other\ FIUs','REs','Other\ financial\ gateway','Criminal\ investigation\ gateway'\}.$$

If one organization is part of another, I assumed no institutional distance.[29] If two organizations do not communicate with each other, I assumed that this is due to an absolute institutional distance. Therefore, $d(i,i) = 0$, $0 < d(i,j) < 1$, if $i \neq j$ and $d(i,j) = 1$, if i and j are not connected.

Let us further assume that all the entities involved in combating money laundering contribute the same amount of output to the AML pool of information. Next to the information potential of the reporting entities, the other financial and criminal gateways, the FIU, the Police, the Public Prosecutor's Office (PPO) and the Courts are specialized bodies whose expertise is added to the national pool of AML information once they are involved. For mathematical parsimony reasons, I normalized the contribution of each of these organizations or groups of organizations to 1. The value of the information provided to the AML network by each organization as $v(i) = 1$, where

$$v: \{'FIU', 'Police', 'PPO', 'Court'\} \cup \{'Other\ FIUs', 'REs', 'Other\ financial\ gateway', 'Criminal\ investigation\ gateway'\} \rightarrow \mathbb{R}^+.$$

I assumed that information flows unidirectional from i to j. In what concerns j, the value of its information depends on what it already has and on what it receives from i. The latter depends on the information value of i and on what is received by j, when the two communicated, as equation 2.1 shows:[30]

$$v(j) = 1 + \sum_{i=1}^{m} v(i)|f(i,j)| \qquad (2.1)$$

Just as Shannon's measure of entropy, Equation 2.2 (presented below) measures the potential information contained in messages transmitted among two organizations that are at an institutional distance $d(i,j)$ from one another. Figure 2.1 plots the function f,[31] where

$$f: (\{'FIU', 'Police', 'PPO', 'Court'\} \cup \{'Other\ FIUs', 'REs', 'Other\ financial\ gateway', Criminal\ investigation\ gateway'\})^2 \rightarrow \mathbb{R}^+$$

$$f(i,j) = -\sum_{ij}^{nXn} d(i,j) ln(d(i,j)) \qquad (2.2)$$

[29]Intuitively, a group (whether an organization or a country) shares an identity. Therefore, within a group, individuals are more homogenous in terms of cognition and obedience to norms and regulations, than individuals across groups.
[30] In equation 2.1 I used the absolute value of $f(i,j)$ to be able to add the two – for visual purposes.
[31]In Shannon's formula, the *'probability of an event occurring'* was substituted with *'institutional distance'* on the OX axis and the *'potential entropy from event realization'* with the *'potential information transmission at a given institutional distance'* on the OY axis.

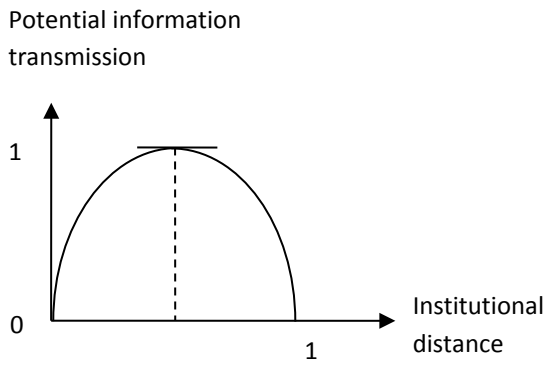

Figure 2.1: Potential information transmission at a given institutional distance.

With zero institutional distance $d(i,j) = 0$, the information contained in the messages received by j is null, $f(i,j) = 0$.[32] Intuitively, since j is institutionally the same as i, (*i.e.* has the same knowledge, brings in the same expertise to the AML information pool) messages received from i do not have the power to increase the informational value of j. In a similar way, when two organizations have no direct link, their institutional distance is $d(i,j) = 1$ and, thus, $f(i,j) = 0$. The reasons for this, is that communication will simply not happen in the absence of a communication channel.[33] Also, when the institutional distance is extremely large, $d(i,j) \to 1$, the messages received by j are perceived as random, which means that these messages do not have the potential to convey an information that would increase the informational value of j. Intuitively, a large institutional distance blocks the information embedded in a message in the same way a large language barrier would. Finally, at an average institutional distance, when $d(i,j) = 0.5$, the message is on average well decoded and also on average contains novel information. Figure 2.1 shows that $d(i,j) = 0.5$ maximizes the potential information transmission, with $f(i,j) = 1$. In other words, at $d(i,j) = 0.5$ the information received by j from i is perceived as valuable and new. This is, of course, the ideal case and persistent departures from it cause information to lose value upon transmission.

Henceforth, I addressed the components of the institutional distance: the regulatory, the normative and the cognitive distances distinguished by Kostova (1997).

In the context of the communication between agencies countering money laundering, I assumed governmental ineffectiveness as means to increase the regulatory distance between these agencies, corruption as means of increasing the normative distance, and liaison officers

[32] $\lim_{x \to o} x \ln(x) = 0$

[33] Falling back on Shannon's measure of entropy, this is the case when P(X)=0.

as means to decrease the cognitive distance among them.[34] These proxies of institutional distance allowed me to quantify the social component that affects the valorisation of information when this information is hierarchically transmitted among law enforcement agencies involved in countering money laundering.

Let δ and γ denote the exogenously determined governmental ineffectiveness, and respectively, corruption.[35] Governmental ineffectiveness artificially increases the institutional distance above optimal point: $d(i,j;\delta) \gg 0.5 \Longrightarrow f(i,j;\delta) \ll 1$. In a similar way, corruption increases the institutional distance between the corrupt agency or group of agencies and their communication partners. For instance, when organization i cooperates corruptly with organization j, i purposefully keeps relevant new information from being transmitted and thus $d(i,j;\gamma) \ll 0.5 \rightarrow f(i,j;\gamma) \ll 1$. Concentrating power in the hands of too few allows for corrupt practices to go un-noticed, since corrupt practices take place easier within *'closed doors'* than otherwise. Checks and balances can be efficient only when powers are distributed (*Cf*. Keefer & Stasavage, 2002).[36] Furthermore, in practice, organizations charged with combating money laundering make use of liaison officers from other organizations to lower the institutional distance between them. If these organizations are already optimally communicating, such liaison officer would actually not only be inefficient, but in the presence of governmental ineffectiveness or corruption, using liaison officers can actually reduce the institutional distance back towards the optimum point, such that $d(i,j;\delta,liaison) \searrow_{0.5} \Longrightarrow f(i,j;\delta,liaison) \nearrow^{1}$.

Finally, let $\sum_{i=1}^{m} v(i)$measure the amplitude of the information distribution of the national AML network – the sum of valuable information held by the organizations engaged in the fight against money laundering. In this chapter, this information distribution amplitude is considered the best measure of effective communication, since repression is not only achieved in court, but also along the repression chain. In the absence of any sharing of information, the amplitude of the information distribution among national AML organizations is $\sum_{i=1}^{m} v(i) = 8$. This follows from the construction of the information value that each organization contributes. Conversely, the circulation of information increases the information distribution and the differences in information sharing leads to different amplitudes. Consequently, the levels of governmental inefficiency and corruption that exist in a particular

[34]In the context of ensuring effective AML policies, the relevance of good governance is discussed by Van den Broek and Addink (2013). The authors argued that good governance principles – proper administration, transparency, participation, effectiveness, accountability and human rights – provided a good framework for the study and design of AML policies.

[35] The assumption is that $0 \leq f_{\delta} = f(i,j;\delta) \leq 1$ and $0 \leq f(i,j;\gamma) \leq 1$ and $f(i,j;\gamma) < f(i,j;\delta)$.

[36] Governmental ineffectiveness only decreases effective communication when the starting point is the optimal one. Alternatively, the split-off of an organization into multiple organizations for the purpose of specialization increases the value of information circulated between them even in the presence of governmental ineffectiveness. Similarly, splitting-off an organization from fear of weak checks and balances may be beneficial for the overall effectiveness of communication when governmental ineffectiveness is low.

country set the stage for how effective information sharing will be among organizations involved in the AML fight. Similarly, the amplitude of the information distribution depends on the correct use of liaison officers and on the information sharing type that the country has put in place.

With regard to the things presented above, in this chapter I tested the hypothesis that *countries where the amplitude of the informational distribution is high have, all else equal, more convictions for money laundering.* In other words, this chapter tests whether countries where AML agencies have effective communication channels, also have significantly higher statistics on convictions for money laundering.

4. Data and methods

4.1. Measures of effective communication among organizations fighting money laundering

The ECOLEF study (2013, pp.174-214) composed 27 individual AML information diagrams for the then EU Member States.[37] These national diagrams reflected the interaction between the national agencies involved in the AML efforts and ranged from very complicated to parsimonious, depending on the size of the country, the organizations created for the purpose of fighting money laundering and more. On the basis of these diagrams I distilled four basic typologies of information sharing present in the EU: the linear, the star, the police and the judicial type. They reflect four simplified models of unidirectional[38] flow of information from the reporting entities and from the own sources of the Police towards the Prosecution and the Judiciary.

In the linear type, the FIU is an independent organization with its own separate premises,[39] whose staff has different education and on-the-job training from that of the Police and of the PPO. The FIU receives information from the national obliged entities, from foreign FIUs and potentially from other state agencies whose suspicion is triggered while conducting their own activities. The FIU then filters this information, and forwards what is relevant to one law enforcement agency. I further distinguished two sub-types of diagrams, depending on which

[37] The information needed to draw these diagrams was gathered over the period of 3 years (from 2010 to 2013). Although appropriate for the analysis of the current chapter, starting from 2014, the Hungarian and the UK diagrams are certainly no longer up to date.

[38] Information flows are not only unidirectional. The Police and the prosecution can request information from the FIU as supporting evidence (*Cf.* ECOLEF, 2013, p.204). Since this alternative did not often surface as common practice of the PPO during the ECOLEF research, I did not incorporate it into the model. Attention should be paid to this practice.

[39] The exceptions were Bulgaria – where the FIU was an administrative unit of the Secret Service, and Greece – where the FIU was a unit of the Hellenic Anti-Money Laundering, Counter Terrorism Financing and Source of Funds Investigation Authority (*Cf.* ECOLEF, 2013, pp.145-147). They too employed staff that was different from that of the police and of the prosecution.

agency the FIU forwards its reports to: the linear-police diagram and the linear-prosecutorial diagram (Fig. 2.2). Next to the financial gateways, information enters this diagram also through the criminal investigation gateways. The Police thus gather information from its sources (informants, on-going investigations etc) and forward it to the prosecutor. Finally, the prosecutor filters this information and presents what is relevant to the courts to secure a conviction.[40] The linear type is present in Belgium, Bulgaria, France, Greece, Malta, Romania and Spain.

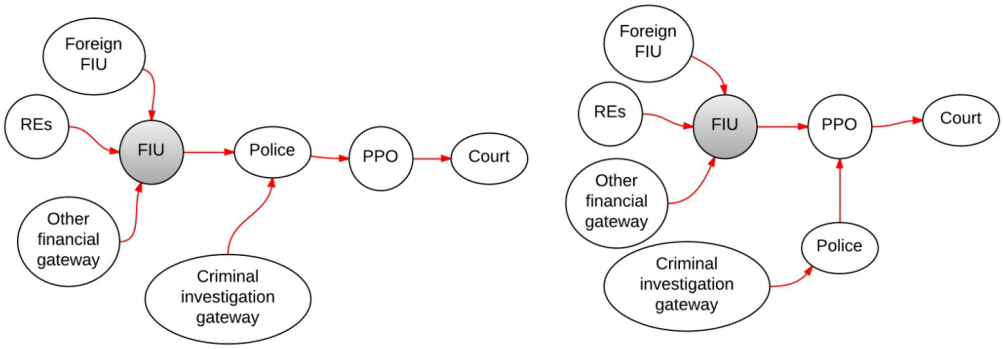

Figure 2.2: A graphical description of the linear information sharing types: a linear-police diagram where the FIU forwards information to the Police and not to the Prosecution (on the left hand side) and a linear-prosecutorial diagram where the FIU forwards the filtered information to the Prosecution and not to the Police (on the right-hand side). The arrows mark the directional flow of information – from the gateways to the courts. Each bullet represents one organization (FIU, PPO, Police or Courts) or a group of organizations with similar roles. Obliged entities are grouped under the heading 'REs'; intelligence from abroad that is forwarded to the FIU is represented under the heading 'Foreign FIUs'; the bullet 'Other financial gateway' includes information provided by national entities that are not obliged entities; the bullet 'Criminal investigation gateway' groups all information that the Police receives own sources (see Section 3).

In the star information sharing type: the FIU is a unit of the Ministry of Finance,[41] employs staff that has different education and on-the-job training from the staff employed by the Police and the PPO. In contrast to the linear information sharing type, the FIU forwards what is relevant to the PPO and to the Police, at the same time and to an equal extent (Fig. 2.3). The star information sharing type is present in the Czech Republic, Hungary, Italy, the Netherlands, Poland and Slovenia.

[40]For simplicity purposes, I grouped under one heading courts of different instances, criminal and administrative courts and investigative judges.

[41] The exceptions were Hungary – where the FIU was an administrative unit of National Tax and Customs Authority, and Italy – where the FIU was a unit of the Italian Central Bank (*Cf*. ECOLEF, 2013, pp.145-147). They too employed staff that was different from that of the Police and of the PPO.

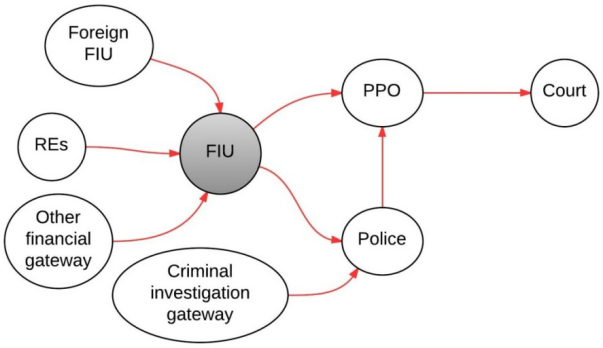

Figure 2.3: A graphical description of the star information sharing type where the FIU forwards information both to the Police and to the Prosecution.

In the police information sharing type: the FIU is a unit of the Police and thus, its staff have police training (*cf.* ECOLEF, 2013, pp.145-147). Whatever information the FIU receives from the reporting entities, from other FIUs or from other financial gateways,[42] it keeps internally (*i.e.* within the Police forces). These, in turn, send the information to the PPO, after having filtered it (Fig. 2.4). The Police information sharing type is present in Austria, Estonia, Finland, Germany, Ireland, Lithuania, Portugal, Slovakia, Sweden and the United Kingdom.

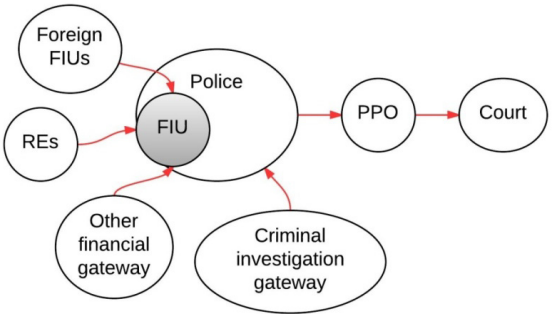

Figure 2.4: A graphical description of the police information sharing type where the FIU is a unit of the Police.

In the judicial information sharing type: the FIU is a unit of the PPO, and, its staff have prosecutorial training. Moreover, among the FIU staff there are active prosecutors (*cf.* ECOLEF, 2013, pp.145-147). The information received by the FIU[43] is kept internally, within the PPO

[42] An argument was made in the IMF (2004) report, that police FIUs would receive less information from what I depicted as 'Other financial gateways' since the Police are perceived as a repressive organization. In lack of evidence, I did not address this point in the analysis.

[43] Again, judicial FIUs may receive less information from what I depicted as 'Other financial gateways' as well as the reporting entities since they are perceived as a repressive organization (IMF, 2004).I did not address this point in this analysis.

(Fig. 2.5). The prosecutors then, receiving also information from the Police present the information further to the Judiciary. The judicial information sharing type is present in Cyprus, Denmark, Latvia and Luxembourg.

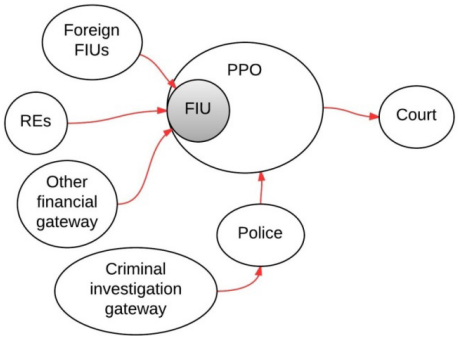

Figure 2.5: A graphical description of the judicial information sharing type where the FIU is a unit of the PPO.

As stated earlier, I am not interested in what courts ultimately receive, but in what law enforcement agencies, in general, know – *i.e.* the information distribution amplitude. Consequently, Table 2.1 reveals the information distribution amplitude of the different information sharing types, after applying equation 2.1. The star and the linear-police network are identical and have the highest information dispersion amplitude, while the judicial information sharing type has the lowest information dispersion amplitude. Table 2.1 also shows that the way cooperation, in the form of information sharing, is organized impacts the information dispersion amplitude of the AML network. So, although the mechanisms for communication exist in all information sharing types, the knowledge possessed by the Police differs. This would matter for effectiveness if the Police were the agency best able (in terms of resources and powers) to take punitive measures.[44]

Table 2.1: Information distribution amplitude when the value of information received depends on the institutional distance [a] between transmitting and receiving organizations

	Linear-police	Linear-judicial	Star	Police	Judicial
Foreign FIUs	1	1	1	1	1
Reporting Entities	1	1	1	1	1
Other financial	1	1	1	1	1

[44]Assuming that information would flow bi-directionally, this situation would still be ineffective as the prosecution would need to dedicate resources to take a pivotal role for this information and to make sure it reaches the Police.

gateways					
Criminal investigation gateway	1	1	1	1	1
FIU	$3f_\delta + 1$	$3f_\delta + 1$	$3f_\delta + 1$	$3f_\delta + 1$	$3f_\delta + 1$
Police	$1 + 2f_\delta + 3{f_\delta}^2$	$f_\delta + 1$	$1 + 2f_\delta + 3{f_\delta}^2$	$4f_\delta + 1$	$f_\delta + 1$
PPO	$1 + f_\delta + 2{f_\delta}^2 + 3{f_\delta}^3$	$1 + 2f_\delta + 4{f_\delta}^2$	$1 + f_\delta + 2{f_\delta}^2 + 3{f_\delta}^3$	$1 + f_\gamma + 4\gamma f_\delta$	$1 + 4f_\delta + {f_\delta}^2$
Court	$1 + \delta + \delta^2 + 2\delta^3 + 3\delta^4$	$1 + f_\delta + 2{f_\delta}^2 + 4{f_\delta}^3$	$1 + f_\delta + {f_\delta}^2 + 2{f_\delta}^3 + 3{f_\delta}^4$	$1 + f_\delta + f_\gamma f_\delta + 4f_\gamma {f_\delta}^2$	$1 + f_\gamma + 4f_\gamma f_\delta + f_\gamma {f_\delta}^2$
Information distribution amplitude	$\mathbf{8 + 7}f_\delta + \mathbf{6}{f_\delta}^{\mathbf{2}} + \mathbf{5}{f_\delta}^{\mathbf{3}} + \mathbf{3}{f_\delta}^{\mathbf{4}}$	$\mathbf{8 + 7}f_\delta + \mathbf{6}{f_\delta}^{\mathbf{2}} + \mathbf{4}{f_\delta}^{\mathbf{3}}$	$\mathbf{8 + 7}f_\delta + \mathbf{6}{f_\delta}^{\mathbf{2}} + \mathbf{5}{f_\delta}^{\mathbf{3}} + \mathbf{3}{f_\delta}^{\mathbf{4}}$	$\mathbf{7 + 5}f_\delta + f_\gamma + \mathbf{5}f_\gamma f_\delta + \mathbf{4}f_\gamma {f_\delta}^{\mathbf{2}}$	$\mathbf{7 + 5}f_\delta + f_\gamma + {f_\delta}^{\mathbf{2}} + \mathbf{4}f_\gamma f_\delta + f_\gamma {f_\delta}^{\mathbf{2}}$

Note. [a] $f_\delta = f(i, j; \delta)$ and $f_\gamma = f(i, j; \gamma)$.

Information sharing types do not however, tell the whole story. In practice, other national factors also play a role in diminishing the information transmission potential among AML organizations. For instance, in some countries, liaison officers are made use of, while in other countries, policy makers have obliged the reporting entities to report to several agencies involved in the AML efforts. Consequently, some of these national particularities have been taken into account when constructing the measure of information distribution amplitude in the 27 EU Member States (Table 2.2).

Table 2.2 reveals for each Member state its information sharing type and its information distribution amplitude. I used Kaufmann, Kraay and Mastruzzi's (2010) indicators on government effectiveness and the control of corruption (Table A2.6) as proxies for $f(i, j; \delta)$ and $f(i, j; \gamma)$. Table A2.1 reveals the calculated national measures of information dispersion amplitude for the 27 EU Member States.

Table 2.2: Information distribution amplitudes in the 27 EU Member States – calculated on the basis of the information sharing types and the presence of liaison officers.

	Information sharing type	Reasons for classification	Measure of the information distribution amplitude
AT	Police	police FIU	$V_{AT} = 7 + 5f_{\delta_{AT}} + f_{\gamma_{AT}} + 4f_{\delta_{AT}}f_{\gamma_{AT}} + 4f_{\gamma_{AT}}f^2_{\delta_{AT}}$
BE	Linear (judicial)	Independent FIU with PPO & Police liaisons	$V_{BE} = 9 + 11f_{\delta_{BE}} + 4f^2_{\delta_{BE}} + f^3_{\delta_{BE}}$
BG	Linear (police)	FIU within SANS; sends mostly to SANS and Police; receives feedback from PPO	$V_{BG} = 8 + 7f_{\delta_{BG}} + 6f^2_{\delta_{BG}} + 5f^3_{\delta_{BG}} + 3f^4_{\delta_{BG}}$
CY	Judicial	FIU head a detached prosecutor; includes detached policemen and prosecutors	$V_{CY} = 8 + 5f_{\delta_{CY}} + 2f_{\gamma_{CY}} + 4f_{\delta_{CY}}f_{\gamma_{CY}}$
CZ	Star	FIU within Ministry of Finance has cooperation protocol with Police AML unit (not a liaison type)	$V_{CZ} = 8 + 7f_{\delta_{CZ}} + 6f^2_{\delta_{CZ}} + 5f^3_{\delta_{CZ}} + 3f^4_{\delta_{CZ}}$
DK	Judicial	FIU has active prosecutors and police officers investigating and prosecuting money laundering	$V_{DK} = 8 + 5f_{\delta_{DK}} + 2f_{\gamma_{DK}} + 4f_{\delta_{CY}}f_{\gamma_{DK}}$
EE	Police	police FIU	$V_{EE} = 7 + 5f_{\delta_{EE}} + f_{\gamma_{EE}} + 5f_{\delta_{EE}}f_{\gamma_{EE}} + 4f_{\gamma_{EE}}f^2_{\delta_{EE}}$
FI	Police	police FIU; PPO and Police have difficult relationship [b]	$V_{FI} = 7 + 5f_{\delta_{FI}} + \frac{f_{\gamma_{FI}}}{2} + \frac{5}{2}f_{\delta_{FI}}f_{\gamma_{FI}} + 2f_{\gamma_{FI}}f^2_{\delta_{FI}}$
FR	Linear (judicial)	Independent FIU, with PPO and Police liaison	$V_{FR} = 9 + 11f_{\delta_{FR}} + 4f^2_{\delta_{FR}} + f^3_{\delta_{FR}}$
DE	Police	police FIU	$V_{DE} = 7 + 5f_{\delta_{DE}} + f_{\gamma_{De}} + 5f_{\delta_{DE}}f_{\gamma_{DE}} + 4f_{\gamma_{DE}}f^2_{\delta_{DE}}$
EL	Linear (judicial)	Independent FIU, headed by detached prosecutor	$V_{EL} = 9 + 11f_{\delta_{EL}} + 4f^2_{\delta_{EL}} + f^3_{\delta_{EL}}$
HU	Star	Even when the FIU first sends to Tax and then they forward to PPO it's still 3 different participants	$V_{HU} = 8 + 7f_{\delta_{HU}} + 6f^2_{\delta_{HU}} + 5f^3_{\delta_{HU}} + 3f^4_{\delta_{HU}}$
IE	Police	police FIU; double reporting - to HRMC and FIU; but HRMC is not Police or PPO;	$V_{IE} = 7 + 5f_{\delta_{IE}} + f_{\gamma_{IE}} + 5f_{\delta_{IE}}f_{\gamma_{IE}} + 4f_{\gamma_{IE}}f^2_{\delta_{IE}}$
IT	Star	Independent FIU sends to Police and PPO	$V_{IT} = 8 + 7f_{\delta_{IT}} + 6f^2_{\delta_{IT}} + 5f^3_{\delta_{IT}} + 3f^4_{\delta_{IT}}$

LV	Judicial	FIU has active prosecutors and is part of the PPO	$V_{LV} = 7 + 5f_{\delta_{LV}} + f_{\gamma_{LV}} + 4f_{\delta_{LV}}f_{\gamma_{LV}} + f^2_{\delta_{LV}}(1 + f_{\gamma_{LV}})$
LT	Police	police FIU	$V_{LT} = 7 + 5f_{\delta_{LT}} + f_{\gamma_{LT}} + 5f_{\delta_{LT}}f_{\gamma_{LT}} + 4f_{\gamma_{LT}}f^2_{\delta_{LT}}$
LU	Judicial	FIU within the PPO; with Police liaison;	$V_{LU} = 8 + 5f_{\delta_{LU}} + 2f_{\gamma_{LU}} + 4f_{\delta_{LU}}f_{\gamma_{LU}}$
MT	Linear (judicial)	Independent FIU with Police liaison; forwards to Police;	$V_{MT} = 9 + 10f_{\delta_{MT}} + 6f^2_{\delta_{MT}} + 4f^3_{\delta_{MT}}$
NL	Star	Independent FIU with Police liaison; STR database is available to all law enforcement agencies	$V_{NL} = 9 + 10f_{\delta_{NL}} + 6f^2_{\delta_{NL}} + 4f^3_{\delta_{NL}}$
PL	Star	Independent FIU sends to Police and PPO both	$V_{PL} = 8 + 7f_{\delta_{PL}} + 6f^2_{\delta_{PL}} + 5f^3_{\delta_{PL}} + 3f^4_{\delta_{PL}}$
PT	Police	police FIU	$V_{PT} = 7 + 5f_{\delta_{PT}} + f_{\gamma_{PT}} + 5f_{\delta_{PT}}f_{\gamma_{PT}} + 4f_{\gamma_{PT}}f^2_{\delta_{PT}}$
RO	Linear (judicial)	Independent FIU sends to PPO (could also send to Police)	$V_{RO} = 8 + 7f_{\delta_{RO}} + 6f^2_{\delta_{RO}} + 4f^3_{\delta_{RO}}$
SK	Police	police FIU	$V_{SK} = 7 + 5f_{\delta_{SK}} + f_{\gamma_{SK}} + 5f_{\delta_{SK}}f_{\gamma_{SK}} + 4f_{\gamma_{SK}}f^2_{\delta_{SK}}$
SL	Star	Independent FIU; sends to Police and PPO	$V_{SL} = 8 + 7f_{\delta_{SL}} + 6f^2_{\delta_{SL}} + 5f^3_{\delta_{SL}} + 3f^4_{\delta_{SL}}$
ES	Linear (police)	Independent FIU; with Police liaison; FIU sends to Police	$V_{ES} = 9 + 10f_{\delta_{ES}} + 6f^2_{\delta_{ES}} + 4f^3_{\delta_{ES}}$
SE	Police	police FIU	$V_{SE} = 7 + 5f_{\delta_{SE}} + f_{\gamma_{SE}} + 5f_{\delta_{SE}}f_{\gamma_{SE}} + 4f_{\gamma_{SE}}f^2_{\delta_{SE}}$
UK	Police	police FIU	$V_{UK} = 7 + 5f_{\delta_{UK}} + f_{\gamma_{UK}} + 5f_{\delta_{UK}}f_{\gamma_{UK}} + 4f_{\gamma_{UK}}f^2_{\delta_{UK}}$

Note. Adapted from ECOLEF (2013, pp.138-220); [a] explain the column; [b] In Finland, the Police (of which the FIU is part) and PPO had a historically high institutional distance. I operationalised this by using $F\left(i, j; \frac{\gamma}{2}\right)$ in the case of Finland.

4.2. Measures of effective repression of money laundering

There are several measures of the effectiveness of the repression of money laundering: the rate with which money laundering is reported – *e.g.* by means of recoded suspicion reports; the rate with which money launderers are incriminated and convicted – *e.g.* the number of prosecutions and convictions for money laundering; and the rate with which money launderers are stripped of their proceeds from crime – *e.g.* the amounts seized and confiscated from money launderers.[45] Figure 2.6 illustrates three measurements of effective

[45] Recommendation 32 of the Financial Action Task Force states *"Countries should ensure that their competent authorities can review the effectiveness of their systems to combat money laundering and terrorist financing systems*

repression, as suggested by the FATF (2004) next to their operationalization – as indicated by ECOLEF (2013) and Eurostat (2013). Since our analysis is based on the effective communication among law enforcement agencies after suspicion is triggered, we cannot use number of suspicion reports are measure of effective repression. At most, the number of suspicion reports can be used to correct for differences in the level of suspicion triggering across the EU (Fig. 2.6).

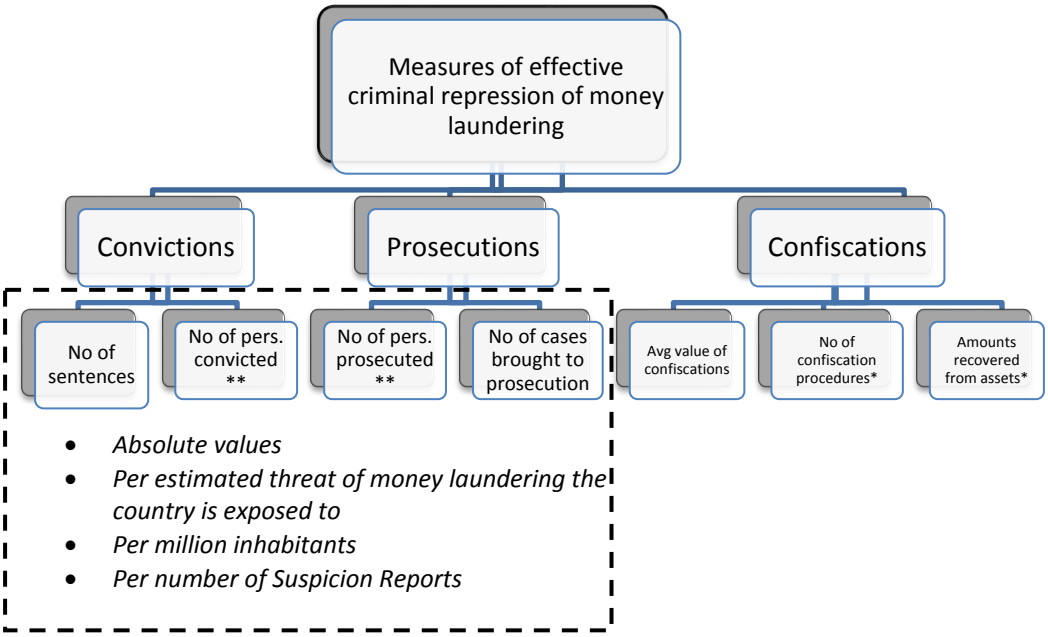

Figure 2.6: Measures of effective criminal repression of money laundering – composition, availability and aggregation. Indicators (*) are collected by Eurostat (2013) but not made available. Indicators (**) are aggregated. The dotted contour encapsulates the variables that I use as proxies for effective repression of money laundering. These measures are used in absolute terms as well as in relation to the money laundering threat, the number of registered suspicion reports, and the size of the country.

Both ECOLEF (2013, p.252) and Eurostat (2013, p.72) reported the number of criminal and administrative sentences imposed for money laundering.[46] Eurostat (2013, p.68) also reported the number of persons involved in these convictions on money laundering in 23

by maintaining comprehensive statistics on […] the STR received and disseminated; on money laundering […] investigations, prosecutions and convictions; on property frozen, seized and confiscated […]" (FATF, 2004, p.11).

[46] Significant differences existed between the data reported for Cyprus, the Czech Republic, Estonia, France, Hungary, Latvia, Lithuania, the Netherlands, Poland and Slovakia in the two reports. Throughout the merging of datasets, where differences existed, I chose the ECOLEF (2013) data.

Member States (exception being Denmark, Greece, Ireland and the Netherlands).[47] Data on the number of prosecutions is similarly operationalised by ECOLEF (2013) and Eurostat (2013). Additionally, ECOLEF (2013, p. 503) provided data on the number of persons involved in the money laundering prosecutions in 10 Member States. Given the many missing observations, I have merged the two measures: *'number of (legal/ natural) persons involved in money laundering convictions'* as measured by ECOLEF (2013) and the *'number of (legal/ natural) persons involved in money laundering prosecutions'* as measured by Eurostat (2013) into one measure *'the number of persons prosecuted/convicted for money laundering'*. Last and unfortunately least available data is on the amounts confiscated. Eurostat (2013, p.16) collected data on two indicators from less than half of the EU Member States while ECOLEF (2013, p.299) reported a yearly average value for confiscations for only 3 Member States.

Figure 2.6 shows that although the measures of effective criminal repression are conceptually intuitive, in practice, they are often easily mixed, often confusing and unfortunately largely incomplete.[48] In order to create a more complete dataset I have merged the ECOLEF (2013) and the Eurostat (2013) data and have averaged it by country over the years 2008-2010 (Table A2.2). Moreover, the *'average convictions'* measure is a simple average of the first two measures: *'average persons'* and *'average sentences'* (Fig. 2.6). The resulting sample is a small, cross-sectional, unbalanced dataset (the number of member states N<30; information on the *'average persons'* is missing for Denmark, Greece and the Netherlands; and information on the *'average sentences'* is not collected in Belgium.

4.3. Correlation analysis

Two variables are considered to be independent as to their probability if information about one variable does not change the probability of the other. It is by convention that if two variables are independent, the measure of association between them is zero. To measure association of effective information sharing and effective repression I made use of Pearson, Spearman rank and Kendall rank correlations (see discussion in the Appendix). Given the size of my database, I did not make use of the newer information-based nonparametric exploration methods, as proposed by Reshef, Reshef, Finucane, Grossman, McVean and Turnbaugh (2011).

I also made use of bivariate regression analysis, taking the form of equation 2.4. I used a logarithmic transformation to normalize the distribution of my effective repression measures.

$$ln(effectiverepression) = \beta_0 + \beta_1(effective\ information\ sharing) + \varepsilon \qquad (2.4)$$

[47] I am aware that in the context of international cooperation – especially taking account the work of the EuroJust in trans-border criminality – this measure of output would not correctly account for money laundering cases where investigation was conducted in several countries and where conviction was secured in another. Nevertheless, I did not account for this possibility in this chapter.

[48] Chapter 3 argues that European statistics on money laundering must be treated with care.

5. Results

Table 2.3 reports on the Pearson, Spearman and Kendall correlation coefficients, as well as on the regression coefficients, where significant. When only the Pearson correlation was significant, or only the rank correlations were significant, I did not consider this as a sufficiently robust association. Tables A2.3-A2.5 control for country effects and Figures A2.1-A2.11 plot the measure of effective information sharing next to the measures of output with which they significantly correlate. This allowed me to spot the outliers (possibly) driving the results. In the case of the correlation between my measure of effective information sharing and the *'average persons prosecuted or convicted'*, the *'average number of suspicion reports',* the '*number of sentences per billion of threat'* and the *'number of sentences per million of inhabitants',* (Fig. A2.2, A2.8, A2.9 and A2.11) Belgium and respectively, the Netherlands drove the results. I thus discarded those associations as insignificant.

Table 2.3: Pearson, Spearman, Kendall correlations between information dispersion amplitude and measures of effective repression and coefficients of the bi-variate regressions.

	Pearson	Spearman	Kendall	Regression	#obs
Avg. Convictions	0.333*	0.399**	0.299**	0.357***	27
Avg. persons prosecuted or convicted	0.369*				22
Avg. Sentences		0.341*	0.243*	0.303**	25
Convictions/ bln of threat	0.33*	0.415**	0.299**	0.253***	27
Convictions/mln inhabitants	0.409**	0.382**	0.276**	0.28**	27
Convictions/suspicion reports		0.393**	0.282**	0.232*	27
Persons prosecuted or convicted/ suspicion reports	0.407*	0.385*	0.303*	0.269***	22
Sentences/ bln of threat		0.341*		0.208**	25
Sentences /mln inhabitants				0.226**	25
Threat (in bln of Euros)		0.414**	0.316**	0.105*	27
Avg. no of suspicion reports	0.36*				27

Notes. Only significant correlations and regression coefficients are reported; *p< .1, **p< .05, ***p< .01.

Table 2.3 shows that my measures of effective information sharing and of effective repression are not independent. However, some correlations were not robust. The number of prosecutions for money laundering was not related to my measure of effective information sharing. The relationship between the *'information dispersion amplitude'* and *'average persons prosecuted or convicted', 'sentences per billion of threat'* and *'sentences per million inhabitants'* respectively were not country robust, and were thus discarded. Finally, the *'number of persons prosecuted or convicted per suspicion report'* was correlated with my measure of effective information, but this could also be driven by missing data.

Given my dataset, I could not discuss or argue for causality. I can however, say that countries with higher measures of effective information sharing had significantly higher measures of effective repression: issued sentences for money laundering, convicted or prosecuted number of persons – both in absolute numbers and mitigated by threat of money laundering, country size, and amount of raised suspicion. These associations were both significant and country robust.

Additionally, I looked at which of the information sharing-types found in the European Union produced most convictions for money laundering. For this purpose used log-linear regression of the type: $\ln(\text{effective criminal repression}) = \beta_o + \beta_1 \text{dummy variable} + \varepsilon$, where the dummy variables are the presence of a liaison officer and the presence of a certain information sharing type. Table 2.4 shows that countries where liaison officers were employed had, all else equal, 1.48% more convictions per suspicion report, 1.7% more convictions per million inhabitants and 1.74% more persons prosecuted or convicted per suspicion report. This finding supports the earlier expressed views of Deleanu (2013), who argued that liaison officers are the fastest way to increase the effectiveness of AML policies. Moreover, although the information dispersion amplitude in the linear and star types was higher than in the police and judicial types (Table 2.4), columns 3-5 show that no information sharing type performed consistently better or worse than the star-network, in terms of convictions or prosecutions. I therefore, found no supporting evidence to the opinions expressed on the FIU typologies by the IMF (2004, pp. 9-17).

Table 2.4: Regression coefficients: the effects of employing liaison officers and other information sharing types than the star information sharing type on different measure of criminal repression.

	Liaison officer	Judicial information sharing type	Linear information sharing type	Police information sharing type
Convictions/ mln inhabitants	1.7**	1.71**		
Convictions/ suspicion reports	1.48**			-1.31*
Persons prosecuted or convicted/ suspicion reports	1.74***			
Effective information sharing	0.191***	-0.161*		-0.13*

Notes. Only significant results of the log-linear regressions were reported; *p< .1, **p< .05, ***p< .01.

Alternative explanations and limitations

There are several limitations to this analysis that cannot go overlooked. First of all, when calculating the information transmission potential for every Member State, I did not take into

account several national circumstances – *a.o.* the application of the legality principle, the lack of resources of one or more law enforcement institutions, size of the country, the presence of investigative judges, differences in the application of the 3rd EU Directive (ECOLEF, 2013, pp. 175-220). Secondly, from an econometric point of view, there are the limitations associated with cross-sectional data, wherefrom causality cannot be inferred. Additionally, the number of countries that I analyzed is small, and as such, multivariate regressions are not possible. The problem of endogeneity cannot therefore convincingly be dealt with. Subsequently, from the perspective of the sample construction, the data on money laundering prosecutions, convictions and confiscations in European Union is relatively scarce and varies extremely across the member states. In order to have a more complete EU picture I bundled the available country data. While this may solve the problem econometrically, it generates new questions about what the effectiveness repression measure really measures. Finally, the institutional interdependencies on which the communication among law enforcement agencies was based on may change over time. Nevertheless, for the purpose of this chapter, I assumed otherwise, as I based my analysis on a series of information diagrams composed by ECOLEF (2013) during the period 2010 to 2013, and on a set of statistics on the repression of money laundering in Europe from 2008 to 2010.

6. Conclusions and policy recommendations

In this chapter I looked at one insufficiently developed problem that had the potential to make a difference in the context of combating money laundering, namely the effective information sharing among organizations involved in the AML efforts. I began by noting that the literature measuring the effectiveness of the AML efforts did not take into account the problem of effective communication among law enforcement agencies after suspicion is triggered. Instead, emphasis was placed on the collection and analysis of suspicion reports by the obliged entities and by the FIU. Consequently, effective communication among law enforcement agencies involved in the AML efforts is still very much a black box.

In this chapter I assumed that there exists a social component that affects the valorisation of information when information is shared between organizations that are institutionally different. Consequently, I hypothesized that countries where the information about money launderers is more effectively dispersed among law enforcement agencies are more effective at convicting money launderers. My analysis developed on the information diagrams built for the 27 EU Member States in ECOLEF study (2013, p.164-220). On the basis of these diagrams I was able to identify the main organizations involved in the AML efforts, the information links and the institutional distance between them. Inspired by the findings of network theory – namely that proximity matters for cooperation – I employed Shannon's (1948) theory of

entropy to calculate the potential for information transmission given the institutional distance between the communicating organizations. The method I proposed for measuring the effective information sharing among authorities involved in the AML fight, after suspicion was triggered, was based on minimizing the institutional distance between these organizations while approaching as many institutionally different organizations as possible. Finally, I showed that, countries where law enforcement authorities were better able to share valuable information, once suspicion was triggered, registered, all else equal, significantly more prosecutions and convictions for money laundering.

In terms of implications for the efficiency of the AML policies, this chapter suggested that where cognitive distance impedes cooperation, liaison officers should be used. In my econometric findings, some AML information sharing types performed better than others in terms of information dispersion amplitude, but the most cost efficient strategy was to build human bridges that lowered institutional differences across entities – *e.g.* liaison officers. Furthermore, where the risk existed that deviant interests may significantly decrease the institutional distance – *e.g.* where the FIU is part of the Police or of the PPO – introducing additional checks and balances could lower the institutional distance. The example of Portugal where reporting entities needed to report to both the FIU that was part of the Judicial Police and to the PPO was one example of adequate checks and balances. Thirdly, where regulatory distance between organizations was large, legislators should have taken measures to ensure the opposite. This was consistent with the recommendations of Kristen (*Cf*. ECOLEF, 2013) to increase the priority given to money laundering by law enforcement, to allocate difficult money laundering cases to more specialized prosecutors and to ensure sufficient resources to law enforcement authorities such that they can properly combat money laundering.

More generally, this chapter suggested that the FATF should not ignore the impact of information sharing among law enforcement on the effectiveness of national AML policies. Simply cooperating (on an operational as well as policy-making level) was considered sufficient for the purpose of enforcing the FATF standards. However, only if information could be communicated without any loss of value did courts receive the same amount of information. If however, and more realistically, information lost value when transmitted among different organizations, attention should be paid to the way information transmission is coordinated. Consequently, my recommendation is that information transmission should be coordinated such that it minimizes the institutional distance between the very different organizations involved in countering money laundering. Importantly, I recommend that new Mutual Evaluation assessments ought to be undertaken based on my methodology and findings when assessing and reviewing the effectiveness AML efforts.

Furthermore, in terms of my desired contribution to the literature on the money laundering, judging from the size of the effect I found, addressing the issue of information sharing among

law enforcement will not lead to an overwhelming increase in convictions and prosecutions for money laundering. Nevertheless, as many others have pointed out already (*cf*. Wicks, 2001; Gelemerova, 2008; Unger & Van Waarden, 2009), the key to winning the fight against money laundering is notoriously hard, and we usually feel like pursuing what Gelemerova calls 'a fanciful and distant aim'. This chapter does not hold the key to winning the fight against money laundering. What this chapter did is twofold. First of all, it offered an alternative explanation to why there were so few numbers of convictions and prosecutions for money laundering in Europe and to why these numbers were so different across countries. Secondly, it built a stepping stone towards a more effective European AML strategy.

Finally, on the one hand, one may wonder whether a study on the effectiveness of AML information sharing, will not tip-off criminals and in effect, actually reduce the overall effectiveness of criminal repression. Although an interesting theoretical exercise, I believe that the crucial question relates to the legality of the AML efforts. Consequently, with no analysis, how are evidence-based policy decisions to be made? And without evidence to support these decisions what motivates the resource intensive efforts to counter money laundering? The following chapter deals with the second problem relating to evidence-based policy making: the possibility that the measure of effective repression is biased.

Chapter 3 – Do countries manipulate official statistics on money laundering? Evidence using Benford's law

1. Introduction

Conventional wisdom tells us that countries may strategically manipulate their official statistics. Following a 2004 financial audit, Greece admitted to having lied about the extent of its budget deficit when joining the Eurozone. [49] Following a 2006 leaked statement, Hungary's prime minister admitted to having lied about the state of the economy to win national elections.[50] So, when in 2010, upon publishing the EU statistics on money laundering, Eurostat stated that this data does not "entirely comply with the stringent requirements of the European Statistics Code of Practice",[51] I decided to investigate what the real implications were. In general, strategically manipulated statistics are not easily uncovered because the mechanisms currently in place to check them are not able to effectively distinguish strategic statistics from inaccurate statistics (*cf.* Michalski & Stoltz, 2013, p. 591). In some cases however, it is obvious that some countries have clear benefits from strategically manoeuvring their statistics. Let's take, as a hypothetical example, the case of Liechtenstein. Liechtenstein was blacklisted by the Financial Action Task Force (FATF) in 2000 and was later taken off the blacklist because it had, on paper, sufficiently signalled its willingness to comply. But this was also partly due to information asymmetry – as the international community did not know to what extent Liechtenstein remained, in reality, still pivotal to the global money laundering schemes. All these examples reveal the necessity to not assume away strategic manipulations from countries and political leaders, and to therefore explore official statistics with a critical eye.

At the core of the current global Anti-money laundering (AML) strategy lays the FATF. The main role of this international watch-dog is to create standards of conduct vis-à-vis money laundering and to enforce them worldwide by 'encouraging constructive action' (FATF, 2000). Countries comply with the FATF standards and agree to be evaluated on their efforts to enforce and uphold these standards, fearing of otherwise being blacklisted (*cf*. Masciandaro, Takáts& Unger, 2007). Being blacklisted subjects countries to economic embargo (*i.e.* severe

[49] Barber, T. & Hope, K. (January 13, 2010). Brussels Attacks Greece over False Data, *Financial Times*.
[50] Wagstyl, S. (October 25, 2007). Lies Haunt a Reformer's Grip on Power. *Financial Times*.
[51] Eurostat's European Statistics Code of Practice (downloadable at http://tinyurl.com/p48vspd)

capital restrictions) from the United States and from the latter's trade partners.[52] Unger and Ferwerda (2008) showed how countries genuinely took efforts to avoid landing on the blacklist of the FATF. In order to avoid blacklisting, countries have had to implement significant institutional changes, in a speedy manner, and these changes had to also be reflected in the official statistics on money laundering, in time for the international evaluations.[53]

The literature has been critical towards the effectiveness of the way the global fight against money laundering is organized (*cf*. Takáts, 2007; Gelemerova, 2008; ECOLEF, 2013). Acemoglu and Robinson (2006) and Robinson (2010) argued that institutional change takes place slowly when elites are not responsive to novelty and when they are not overthrown by the novel institutions. In Europe, many of the elites did not embrace the legislative changes proposed by the FATF as necessary for an immediate improvement in the fight against money laundering.[54] Furthermore, as the literature on legal transplants shows (*cf*. Kagan, 2007; Kelemen, 2008), Member States to which these changes were too far from their core legal practices, may be reluctant to absorb and to internalize these changes in a speedy manner. In this context, one may wonder, whether facing institutional persistence, high international pressure to conform, and potential capital bans, governments did not, in fact, act strategically?[55]

In order to analyze this, I used a novel statistical test that is based on the distribution of the first digits of official statistics on money laundering (also known as Benford's law and explained in Section 5) to test the likelihood that these statistics were manipulated. According to Benford's law, if we pick a random sample of numbers representing natural processes, and look at the distribution of the first digits of these numbers, we will see that contrary to popular belief, digit 1 occurs most often, then digit 2, and so on, with digit 9 occurring most in less than 5% of the sample (Benford, 1938). The standard assumption is that without prior

[52] In December 2001, the FATF recommended that its members apply countermeasures to Nauru. See FATF decides to apply countermeasures to Nauru (http:// www1.oecd.org/fatf/pdf/PR-20011205_en.pdf)

[53] In this chapter, the term 'international evaluation' encompasses both a Mutual Evaluations Report (MER) and a Follow-Up Report (FUR).

[54] Next to rating country efforts to combat money laundering, the FATF also put these efforts into perspective, although not always in a meaningful way. In 2010, the FATF expressed its concern about the effectiveness of the German reporting system. The absolute numbers of suspicion reports sent in by the financial sector in Germany was far lower than in France, Canada, the United Kingdom and Italy – countries with comparable financial sectors (FATF, 2010, p.170). The comparison did not however give regard to the much higher requirements for submitting a suspicion report that existed in Germany, for if it had, it would have compared Germany with Denmark and Switzerland and had seen that the financial sector was actually performing much better (Ferwerda, Deleanu, van den Broek & Unger, 2013). The German authorities found the FATF's conclusion alienated from reality but nonetheless adapted to reporting more.

[55] This question has also been addressed by Masciandaro and Portolano (2004), who treated the regulation of money laundering as a product subject to an international demand and supply. The authors argued that the degree of financial laxity of a country was determined by its policy makers through a cost and benefit analysis. They were nevertheless, not able to address the role of international reputation sensitivity in the decision of the policy maker.

knowledge of Benford's law, since people are not intuitively good at creating datasets that follow Benford's distribution (Camerer, 2003), data deviating thereof is likely to indicate irregularities. In light of the principal agent literature (Section 3), I hypothesized that countries with higher cheating incentives had significantly more deviations in their official statistics, independent of their capacity to do good book keeping. To test this, I put together a dataset that reflected the European political thought processes in the matter of fighting money laundering and that pooled together indicators of compliance and efficiency (Section 4). This allowed for a meaningful comparison where Benford's law could be efficiently applied to uncover potential misreporting. I therefore gathered yearly statistics on money laundering from Eurostat, from national Financial Intelligence Units (FIUs) and from Mutual Evaluation Reports (MERs) of the FATF or of Moneyval on 29 indicators from 2003 to 2010 for 27 EU Member States.[56] Section 6 reports on my findings. I noticed that European statistics on money laundering were, to a great extent, unreliable according to Benford's law and that countries reacted strategically to the international community's pressure to put the AML efforts on the top of their national agenda.

Importantly, the contribution of this chapter is fourfold. First of all, it offers a state of the art review of the multidisciplinary literature on Benford's law – from the mathematical proofs to its latest empirical applications. Secondly, it uses insights from the principal agent literature to underpin the uncovering of strategic manipulation of data with the help of Benford's law – as it develops a simple model to describe strategic manipulation of statistics by countries behaving as rational agents under the pressure of international evaluations and sanctions. Thirdly, it pioneers the application of the methodology of Benford's law to the field of money laundering. And fourthly, this chapter is one of the few that uses datasets which satisfy the necessary and sufficient conditions and which allow for the correct application of this methodology.

2. Literature review

2.1. Unreliability of official statistics on crime

Detecting and eliminating fake statistics are crucial not only for policy makers, but also for scientists and the public at large. Imagine the disappointment of a researcher whose hypotheses have been tested on fake data – leading him to confusing or even inaccurate conclusions. Imagine spending tax payers' money to collect statistics that cannot or should not be used to support policy making. Since researching and analysing financial crime, as well as creating policy to tackle them, strongly rely on official crime statistics, crime data has come

[56] Eurostat collects data for European Member States and for accession countries. Data for Romania and Bulgaria, is therefore available, also before 2007.

under scrutiny several times. [57] The literature has put forward three main explanations for unreliable data in general: non-developed economies do not have the capacity to keep reliable statistics (*cf*. Holz, 2003; Judge & Schechter, 2009), survey supported statistics may contain a respondent's bias (Judge & Schechter, 2009), and countries subject to more pressure turn a blind eye to strategic modifications of statistics (Michalski & Stoltz, 2011). Related to the first explanation, Kristen argues that missing data will occur also in developed economies when authorities do not prioritize statistics collection (*cf*. ECOLEF, 2013, pp.164-166).

With respect to the reliability of crime data, most of the doubts relate either to the way the data is collected, or to the political pressures underlying official statistics (Rubin & Babbie, 2011, p.414). In the case of law enforcement statistics, the former argument is most often put forward, whereas the latter worries about data being intentionally falsified are far fewer and more disputed (*e.g.* US National Commission on Law Observance and Enforcement, 1930).

Additionally, what frustrates most researchers (*cf*. Becker, 1973; De Fleur, 1975), is the fact that crime data is biased in such a way that it does not reflect only the size of crime in an area, but also the degree to which law enforcement is willing and able to handle it and the degree of societal need and interest in fighting the crime. [58] It is therefore, unclear whether a high number of money laundering investigations reflects that the country is highly populated with financial criminals or whether law enforcement is just effectively putting in a lot of effort into fighting money laundering, or whether, money launderers are just reported to the authorities swiftly as society has low levels of toleration for this type of crime. Although interesting and relevant, this chapter did not tackle the problem of crime data revealing at the same time crime levels, law enforcement efforts as well as societal tolerance for financial crime. Furthermore, in this chapter, I simply used the term 'statistics on money laundering' to encompass both the money laundering activities, as well as, the AML efforts.

This chapter contributes to the literature on the regulation of money laundering with the pioneering application of a novel methodology that allows us to distinguish between the two formerly introduced sources of error: *'procedural problems'* and *'strategic behaviour'*. This chapter tests the arguments: *'data is unreliable due to procedural problems'* and *'data is unreliable due to countries' strategic behaviour'* and shows that in the case of EU statistics on money laundering, the latter holds. Therefore, this chapter contributes to the financial crime literature and to the regulation literature by shedding light onto a novel method to test the

[57] The US National Commission on Law Observance and Enforcement (1930, p.13) issued a report on Criminal Statistics where it argued that police data has a high probability to be falsified due to laxer legislation on police procedure and due to self-interest pressures: *"The significant fact that cities are beginning to use these reports in order to advertise their freedom from crime as compared with other municipalities suggests at once a difficulty under which the voluntary system of gathering police statistics for national purposes must labor"*. Shortly after, the report was criticized by Davies (1931) who argues that *"cases of deliberate falsification are practically unknown"*.

[58] Although legitimate concerns, this chapter did not deal with the latter bias.

unreliability of official statistics – a method that is independent from previous data assessment methods and that contrary to the latter can distinguish between the two sources of data error. In this sense, it complements the work of Ferwerda *et al.* (2013), and Rubin and Babbie (2011) and opens a new avenue for empirical research in the field of financial crime.

2.2. Multidisciplinary applications of Benford's law

"*Most […] tests of data integrity are investigations of consistency and robustness in various forms"* (Nye & Moul, 2007, p.1). In the case of EU statistics on money laundering, this translated into a number of efforts: (1) to match data across several sources – *i.e.* to ensure that the statistics of different national agencies did not clash; (2) to identify measurement biases – *i.e.* was a suspicious transaction report that banks and other obliged reporting entities had to send to the FIU in one country similar to an unusual transaction report and to a suspicious activity report that they had to file in another country?; (3) to identify econometric specification biases – *i.e.* if the resources of a FIU could not be separated from those of the Police how could its costs be calculated?; and (4) to match data across time – *i.e.* an investigation on money laundering started in December 2013 and ended in January 2014 could be counted twice: in the number of investigations conducted in 2013 and in the number of investigations conducted in 2014.[59]

In the methodological notes accompanying the tables of statistics, Eurostat (2010, 2013) gave details on the efforts it took therein and on the caveats that statistics on money laundering still had. Eurostat did not update its statistics on a yearly basis and research and policy making has therefore often been based on national sources. The most common source for statistics on money laundering – FIU annual reports – nevertheless accompanied their statistics with fewer methodological notes, which suggests that traditional investigations into the consistency and robustness of statistics on money laundering should continue taking place, especially at a national level. However, these tests are, in my view, both costly and give no consideration to the underlying processes generating the data under analysis.

Originally confined to forensic accounting (*Cf.* Nigrini, 1996; Nigrini &Mittermaier, 1997; Drake &Nigrini, 2000), academic interest in uncovering and analyzing statistic misreporting has grown since the late 1990s and expanded to economics, politics and regulation. Supporting the rise of this new corpus of research has been the deeply non-intuitive, yet fascinatingly simple law of Benford, which formalized the frequency distribution of the first digits of naturally generated series of observations. Armed with a novel method to test whether the data generation process of the statistics under analysis had the same randomness as data generation processes that were assumed not to contain human errors, researchers could, relatively cheaply, uncover misreporting of data. The scope for application incorporated, among others, balances of payments (Michalski & Stoltz, 2011), budget deficit

[59] On the basis of Eurostat's European Statistics Code of Practice (downloadable at http://tinyurl.com/p48vspd)

statistics (Rauch, Göttsche, Brähler & Engel,2011; Rauch, Göttsche, Brähler& Krongeld, 2014), political campaign financing (Cho & Gaines, 2007), academic publications (Toedter, 2009; Diekmann, 2007), survey results (Schäfer, Schräpler, Müller & Wagner, 2004; Judge &Schechter, 2009), macroeconomic statistics (Holz,2014; Nye &Moul, 2007; Gonzalez-Garcia &Pastor, 2009) and price fixing (El Sehity, Hoelzl & Kirchler, 2005). This chapter fits within this novel research stream and shows, for the first time, that Benford's law can successfully be applied to the debate on the efficiency of global AML efforts and that it can offer new insights into the political processes underlying and undermining the efficiency of these global efforts.

In my view, researchers have related to Benford's law differently. A first group of researchers saw Benford's law as a tool for agnostics to explore large datasets (*e.g.* Cho & Gaines, 2007; Judge& Schechter, 2009). They had no explicit underlying theory to test. A second group had a set of theoretical predictions about misreporting, and used Benford's law to test these hypotheses (*e.g.* Nye & Moul, 2007; El Sehity *et al.,* 2005). These researchers started from two assumptions: people do a poor job in replicating known data-generating processes (Camerer, 2003) and Benford's law is not widely known by those constructing the data under investigation. With this in mind, Benford's law became a good tool to investigate human driven data unreliability. Finally, a third group (*e.g.* Janvresse & De La Rue, 2004; Gauvrit & Delahave, 2011) abstracted from these assumptions, and instead focused on the universality of the law. I have paid special attention to the latter's comments in Section 5, whereas I will introduce the first two groups here.

Cho and Gaines (2007, p.218) used Benford's law to analyze political campaign finances being motivated by the fact that *"popular and academic accounts of campaign finance are rife with tales of corruption […]".* Their analysis revealed patterns and years which deserved further analysis but they did not go beyond this exploratory attempt. Judge and Schechter (2009) used Benford's law to explore the reliability of certain types of questions and of certain enumerators known to be used in collecting survey data. They argued for eliminating those questions and interviewers who generate the most deviations because of their potential to produce fake data. Furthermore, Judge and Schechter (2009) utilised Benford's law to show that surveys conducted by academics were of higher quality than those conducted by governments. Their conclusion rested however on the study of nine surveys and would profit from being expanded. Alternatively, Schaefer *et al.* (2004) took a similar interest as Judge and Schechter (2009) and used Benford's law to detect the fake interviews and interviewees in the German Socio-Economic Panel survey. The red flags that Benford's law raised corresponded well to the known cheaters. Holz (2014) investigated the Chinese statistics, among allegations that '*a wind of falsification and embellishment*' was going through them (Rawski & Xiao, 2001). In spite of a convincing argumentation of why the Chinese National Bureau of Statistics enjoyed a very favourable institutional framework to cheat, Holz's analysis was plagued by limited data and also lacked theoretical support. His exploratory analysis using Benford's law

revealed no suspicion of falsification, which led him to conclude that there were either no falsified statistics, or the Chinese National Bureau of Statistics knew how to avoid detection.

Exponents of the second group, Nye and Moul (2007) used Benford's law to test the theoretical argument of Summers and Heston (1991) according to which Penn World Tables contained many poor quality macroeconomic indicators. Due to data scarcity, they bundled together OECD and African data and compared the divergence from Benford's law of these two groups. As expected, OECD macroeconomic indicators deviated less, although Nye and Moul (2007) only used Pearson's χ^2 statistic to test for this deviation. And as Cho and Gaines (2007, p.221) pointed out, *"a preferable statistic would be less sensitive to sample size than the χ^2statistic".* Two years later, Gonzalez-Garcia and Pastor (2009) gathered more data and redid the analysis of Nye and Moul (2007) and came to similar empirical conclusions. Nevertheless, this International Monetary Fund (IMF) working paper casted doubts about the accuracy of Benford's law when comparing its red-flags with those expressed in earlier IMF Data Quality Assessments and argued in favour of traditional data investigation techniques. El Sehity *et al.* (2005) used Benford's law as benchmark to test price evolutions in the Eurozone after the introduction of the Euro. If prices genuinely solely reflect market forces, then they should follow Benford's law (El Sehity *et al.,* 2005). Instead, they found strong evidence of 'psychological pricing' and showed that this has had a significant impact on real inflation for different products given their initial proximity to a psychological price immediately after conversion took place. Rauch *et al.* (2011, p.243) took the view that *"like firms, governments might try to make their economic situation seem better".* They used Benford's law to measure country specific deviation of macroeconomic data relevant in determining whether European Member States comply with the deficit criteria set by the Stability and Growth Pact. Instead of focusing on identifying those countries that significantly differed from Benford's law, Rauch *et al.* (2011, p.245) ranked countries according to the extent to which they diverged, arguing that "*the position of each individual country in this ranking helps to determine in which order and to what extent further auditing procedures should be carried out*". Their analysis showed, without a doubt, that Greece – a country plagued with allegations of deficit data falsifications – was the first to need an audit. Later, Rauch, *et al.* (2014) used Benford's law to compare government social security statistics with deficit related data reported by the EU Member States to Eurostat. They illustrated that the deviations of the statistics on social security were considerably smaller than deviations of the statistics on deficits and concluded that *"European governments behave in accordance with the incentives, i.e. while the quality of the social security statistics appears to be higher, there is a widespread tendency to report incorrect deficit data"* (Rauch, *et al.*, 2014, p.147). Based on this, they also concluded that their results validated the effectiveness of Benford's law as a tool that identifies manipulated data. Finally, Michalski and Stoltz (2011, p.592) used Benford's law to test the hypothesis that "*a country may want to hide its true state of the world to prevent capital outflows or attract inflows".* For this purpose, they grouped countries according to their exchange rate regimes,

foreign asset and current account balance positions, and according to their vulnerability to capital flow reversals and showed that, indeed, countries that had extra financial incentives to cheat, also had balances of payments with significantly higher deviations from Benford's law.

The latter research offers, in my view, a more promising approach to studying data anomalies due to its more robust methodological underpinning. In this chapter, I consequently take a similar perspective. I make use of deviations from Benford's law to test the propositions born from a simple one-shot game with incomplete information that is introduced in the following section.

3. The model

A fundamental assumption many economic models make, is that economic agents are rational and have knowledge of the true state of the economy. This neglects the possibility that governments successfully cheat, as the models predict that cheating governments would be unmasked instantly (Manne, 1966). Knowing that they will certainly face punishment, government officials would not even try to cheat (Chow, 2006). However, the literature on one-sided private information shows that revealing partial information may be an equilibrium (*cf*. Crawford & Sobel, 1982; Benabou & Laroque, 1992).

In this chapter, I followed the seminal work of Crawford and Sobel (1982). Crawford and Sobel developed a model of strategic communication in which a better informed expert sent a possibly noisy signal to another agent, who, in turn, took an action that determined the welfare of both. They showed that there were equilibriums in which the agent relied on the expert's possible 'cheap talk'. The likelihood of such equilibrium increased the more similar in preferences the expert and the agent were, the more exogenous experts could confirm the signal and the more the expert and the agent communicated. In this chapter, I studied a one-shot game with incomplete information. Suppose there is a set of countries indexed $i \in \{1, \dots, q\}$, all employing capital K_i and labor L_i. For simplicity, I assumed that labour is immobile, constant and similar across countries ($L_i \equiv 1$). I also assumed capital was mobile and the return on capital equalled its marginal productivity. I further assumed that capital owners were law abiding and did not value black finance.[60] They are therefore influenced in their investments by the warnings of the international community and by the private signals[61] that countries give with respect to their efforts in fighting money laundering.

[60] In Section 2, I argued that crime data reflects at the same time the level of crime, law enforcement efforts and society's tolerance for crime. I assume here non-tolerant investors across the world.

[61] Read: public (private) signals as information about the way future looks that belongs to a person or agency that has (no) better knowledge over the future or possibility to affect it. The distinction public/ private should not be made from a legal perspective here.

When modelling a country's incentives, I relied on the standard assumptions of the literature on communication under one-sided private information. The international community reveals during an evaluation whether the country performs well or not in fighting money laundering. I consider two random variables θ and ρ, normally distributed and independent, in which $\theta_i \in [0,1]$ denotes the results of the international evaluation for country $i \in \{1, \dots, q\}$ and, respectively, $\rho_i \in [0,1]$ measures the degree with which a country signals a fake reality. The case when $\theta_i = 1$marks full-compliance with the FATF standards, whereas $\theta_i = 0$ marks complete non-compliance. When $\theta_i \in (0,1)$ there exists a partial compliance. Section 4, reports on how countries are evaluated using a Likert scale, but for now it suffice to say that evaluation results are modelled as a variable taking any value on a bad to good spectrum. The evaluation result is public information and capital owners and countries alike have this information. Evaluation results cannot be changed ex-post, but countries can privately signal their willingness to conform to international standards before, during and after the evaluation by presenting positive statistics. These statistics can reflect reality but they can also be strategically manipulated to look positive in order to signal future better evaluations and therefore to attract investors. Capital owners will not be able to observe a country's real effort and will have to rely on statistics to estimate it.

The case when $\rho_i = 0$ pertains to country i reporting truthfully on its statistics. The case when $\rho_i = 1$, means that country i radically strategically manipulates its statistics in order to make them more appealing to capital owners. Krishna and Morgan (2004) argued that when capital owners could inquire into the origins of statistics, they can better distinguish fake signals. I took a similar view and argued that private signals do not influence country evaluators to the same extent as they do private investors, as country evaluators can inquire during the evaluation on the origins of the statistics.

Crawford and Sobel (1982) argued that rewarding good signals could induce better information transmission. The concept of *'naming and shaming'* which later echoed in soft law (*Cf*. Braithwaite, 1989; Karpoff, Lott & Wehrly, 2005) stated that negative rewards are imposed in the form of 'reputation loss' for those that are caught with fake signals. In my model therefore, cheating comes at the cost of being uncovered and badly evaluated at a future evaluation, such that $TC_i = \rho_i \frac{C}{(1+\bar{r})^{t_i}}$, where C is the punishment for cheating, t_i is the time distance from the evaluation and $\bar{r}$ is a universal discount rate. Here I assumed that the probability to get caught was directly proportional to the extent to which countries strategically manipulated statistics – such that countries that radically manipulated all statistics were certainly going to be found out, whereas countries that only slightly manipulated statistics, had a chance not to be punished. I also indirectly assumed that supervision is directly proportional to the costs of cheating. Barro and Gordon (1983) pointed

to costs of cheating being directly proportional to the cost of reputation loss.[62] Let then the costs of tampering with statistics depend on past evaluations and on the expectation of future evaluations, such that $C = 2 + \theta_1 - E[\theta_2]$, where θ_1 is the past evaluation and $E[\theta_2]$ is a country's expectation on its future evaluation. The amount of capital each country has will therefore depend on the public signals of the international community and on the country's private signal, $K_i = f(\theta_i, \rho_i)$, such that $K_i = {\theta_i}^{\alpha} + {\rho_i}^{\beta}$, where $\alpha, \beta \in [0,1]$ and represent the elasticities of capital to each of the signals. I assumed these elasticities to be constant across countries.

Each country is interested in attracting capital to ensure its production. I assumed a Cobb-Douglas production function such that $Y_i = {K_i}^{\gamma} {L_i}^{1-\gamma} = K_i$, with $\gamma = 1$ for simplicity reasons. Let π be the return of a country, such that $\pi_i = Y_i - TC_i$. I assumed that each country only cares about its return when deciding whether to tamper with statistics or not, such that it maximizes returns.

Proposition 1: *All else equal, strategic manipulations of statistics will occur most when furthest away from evaluations.*

A rational country that is interested in returns only will face the following optimization problem $max_{\rho}\pi_i = max_{\rho}\left({\theta_i}^{\alpha} + {\rho_i}^{\beta} - \rho_i \frac{C}{(1+\bar{r})^{t_i}}\right)$. This means that the optimal level of statistics tampering country i will undertake is

$$\rho_i = \frac{\beta^{\frac{1}{1-\beta}}(1+\bar{r})^{\frac{t_i}{1-\beta}}}{C^{\frac{1}{1-\beta}}} \tag{3.1}$$

Equation 3.1 shows that, all else equal, a higher t_i implies country i will tamper more with its AML statistics. The current shape of Equation 3.1 is motivated by the fact that $0 \leq \beta \leq 1$.

Proposition 2: *All else equal, in the aftermath of an international evaluation, statistics of money laundering of countries that receive a negative evaluation deviate more from Benford's law than those of countries that received a positive evaluation.*

Knowing that the optimal level of data tampering is

[62] During the 2014 Presidential Address to the Russian Federal Assembly, President Vladimir Putin urged Russian owned foreign capital to return to Russia in a bid to restore a shrinking Russian economy, visibly affected by dropping oil prices and by Western imposed sanctions in relation to the Russian-Ukrainian conflict. With little reputation costs, Putin's offer of full tax amnesty and no questions on the origin of the returning funds came at little cost. (President Putin urges Russian resilience for hard times (BBC News) retrieved from www.bbc.com/news/world-europe-30322198)

$$\rho_i = \frac{\beta^{\frac{1}{1-\beta}}(1+r)^{\frac{t_i}{1-\beta}}}{(2+\theta_1-E[\theta_2])^{\frac{1}{1-\beta}}} \tag{3.2}$$

then, all else equal, a high original evaluation θ_1 will lead to a lower incentive to tamper with official statistics, as the costs associated with the loss of reputation are higher.

Proposition 3: *If, as a result of a round of mutual evaluations, more countries are negatively evaluated, all else equal, aggregate statistics on money laundering will deviate more from Benford's law in the aftermath of the round of mutual evaluations than before.*

Since θ_i is normally distributed on $[0,1]$, it means that $E[\theta_i] = 0{,}5$. Let x_{min} $(1 \leq x_{min} \leq q)$ be the smallest number of countries that needs to be negatively evaluated for Proposition 3 to hold. It follows from Equation 3.2 that if $x_{min} \geq 17$ $(when\ q = 27)$ Proposition 3 holds, if all countries have a time-span to evaluation of two years (see derivation in the Appendix).

4. Data

Following the intuition of Durtschi, Hillison and Pacini (2005), I choose a data set that allows for the detection of misreporting (if any occurs) given my methodology. I therefore looked at statistics that could be manipulated by countries facing international pressures to fight money laundering.[63] These statistics must indeed be used by the international community to restrict capital from flowing into jurisdictions that do not fight money laundering. This data should also theoretically follow Benford's law and moreover it should be comparable across countries.

Through its 40+9 recommendations, the FATF encouraged countries to specifically address the mechanisms known to be used by money launderers, and these statistics were believed to illustrate a country's efforts in combating money laundering.[64] The FATF proposed 40+9 Recommendations but, in fact, only few allow for numerical evidence (Table 3.1), the others referring to substantive legal change. For theoretical considerations, explained in Section 5, I did not expect that time-invariant indicators (number of staff dedicated to fighting money laundering in the FIU, Police, Judiciary etc) or the percentages of suspicion reports (coming from credit institutes, sent to law enforcement, investigated by law enforcement) follow Benford's law. To the contrary, I expected that the number of suspicion reports put forward by different groups of reporting entities, the number of suspicion reports analyzed by law

[63] In the case of some statistics, cheating was easier because it required only national coordination, whereas for others, international coordination was required, and that made cheating more difficult. As robustness check, I analyzed both data.

[64] See FATF (2003) and FATF (2004a) and FATF (2004b) for the forty and nine recommendations and the methodology for assessing compliance respectively.

enforcement, the number of criminal AML investigations, prosecutions and convictions, and the number of correct and incorrect cash declarations filled in at border crossings, and the amounts of cash moved across borders, follows Benford's law. Tables A1 and A2 describe the statistics on money laundering used in this chapter and their availability per country and per year.

My analysis focuses on the 27 EU Member States, deliberately excluding other countries subject to the FATF/Moneyval evaluations. Although a comparison with the US, Australia and other EEA members, for which statistics are readily available is possible and may be warranted, this chapter focuses on the EU Member States – a melting pot of legal cultures,[65] social and economic institutions that have recently been subjected to strong market pressures and have converged in an European fashion (*cf.* Kelemen, 2008). In the period 2003-2010 all EU Member States underwent an evaluation – conducted by FATF or Moneyval representatives – as part of the 3rd Round of Mutual Evaluations. The evaluations were meant to check the extent to which countries complied with the above mentioned recommendations and as a result thereof, countries were awarded one of four qualifications (Table 3.1). The qualifications 'compliant' and 'largely compliant' were considered to be good. If a country received a 'partially compliant', there were serious remedies that the country needed to undertake to signal compliance with the FATF standards. Finally, 'non compliant' was the lowest qualification and would lead to significant international pressure being put on the country to address it, and may ultimately lead to economic sanctions (FATF, 2009b, p.12). I focused on data falling under the FATF's recommendations 13, 16, 27, 31, 32 and special recommendation IX, and therefore Table 3.1 only reports on the qualifications countries received on these six standards.

Table 3.1: Year when the MER was published and the evaluation results on Recommendations 13, 16, 27, 31 and 32 and on Special Recommendation IX by EU Member State.

Country	Publication MER	R13	R16	R27	R31	R32	SR IX
AT	2009	PC	PC	C	C	PC	PC
BE	2005	LC	LC	C	LC	LC	NC
BG	2008	PC	PC	LC	C	PC	PC
CY	2006	C	PC	LC	C	PC	LC
CZ	2007	LC	PC	C	PC	LC	LC
DE	2010	PC	NC	LC	LC	PC	LC
DK	2006	PC	PC	C	LC	PC	PC
EE	2008	LC	PC	C	LC	LC	PC
EL	2007	PC	NC	LC	PC	NC	NC

[65] Belonging to the European Union entails the harmonization of AML policies and implicitly, the standardization of statistics.

ES	2006	LC	PC	LC	LC	PC	LC
FI	2007	LC	PC	LC	LC	PC	PC
FR	2011	PC	PC	LC	LC	PC	LC
HU	2005	PC	PC	LC	C	LC	PC
IE	2006	C	PC	C	LC	PC	PC
IT	2006	PC	NC	C	LC	LC	C
LT	2006	PC	PC	PC	LC	PC	PC
LU	2010	NC	NC	PC	PC	PC	NC
LV	2006	LC	NC	C	LC	LC	NC
MT	2007	PC	PC	LC	C	LC	LC
NL	2011	LC	PC	C	LC	LC	LC
PL	2006	PC	NC	PC	PC	PC	LC
PT	2006	LC	PC	LC	LC	PC	LC
RO	2008	PC	NC	LC	LC	LC	PC
SE	2006	PC	PC	LC	LC	PC	NC
SK	2006	PC	NC	LC	PC	PC	PC
SL	2005	PC	PC	PC	C	LC	C
UK	2007	C	LC	C	C	LC	LC

Notes. In accordance with the 3rd Round of Mutual Evaluations, published by the FATF and Moneyval (downloadable atwww.fatf-gafi.org and www.coe.int/moneyval). C, LC, PC, NC mark compliant, largely compliant, partially compliant and non-compliant.

Focusing exclusively on the EU Member States has an additional advantage. I can make use of Eurostat's official statistics on money laundering. These statistics are provided by the EU Member States, have already been checked for consistency and therefore offer a more reliable dataset.[66] The 2010 Eurostat report contains data from 2003-2008 for the then 27 EU Member States, whereas the 2013 Eurostat report contains data from 2005 to 2010 for EU-27, Candidate countries and EEA countries. When merging the two datasets, I came across several data misfits, and I have consistently chosen the data published in the latter report, as it was likely to contain fewer mistakes. Finally, where Eurostat data was missing, while available in the annual reports of national FIUs and/ or MERs, it was added it to the database. I think this to be a helpful and innocuous fix, despite the fact that I may, in fact, be overlooking fake statistics that were later passed as mistakes or omissions.

5. Methodology

In 1881 astronomer and mathematician Simon Newcomb wrote in an article in the American Journal of Mathematics where he noted that first digits do not appear with equal frequency in

[66] Eurostat's European Statistics Code of Practice (downloadable at http://tinyurl.com/p48vspd)

large sets of 'real-world numbers' – *i.e.* numbers that reflect natural processes. He observed that the leading digits $d \in \{1, \dots, 9\}$ of naturally generated series of observations occur with probability $P(d) = \log_{10}(d+1) - log_{10}(d) = log_{10}\left(1 + \frac{1}{d}\right)$. Table 3.2 presents the frequency of leading digits for a set that follows Benford's law. His observation went against the popular belief that in large datasets, the numbers 1 to 9 should appear with equal probabilities as leading digits. In 1938, American physicist Frank Benford tested the observation of Newcomb, on an own collection of *'real world numbers'* among which population figures, baseball statistics and numbers appearing in Reader's Digest articles (Benford, 1938). Benford found that he could empirically confirm the predictions of Newcomb (1881) very well, and so, although discovered by Newcomb, the law took the name of Benford who popularized it.

Table 3.2: Frequency distribution of leading digits $d \in (1,9)$, according to Benford's law.

d	1	2	3	4	5	6	7	8	9
$P(d)$	30.1%	17.6%	12.5%	9.7%	7.9%	6.7%	5.8%	5.1%	4.6%

5.1. Necessary and sufficient conditions for Benford's law to hold

Benford (1938) did not formally prove the law, and only half a century later, did Hill (1995, p.360) prove that "*if probability distributions are selected at random, and random samples are taken from each of these distributions in any way so that the overall process is scale (base) neutral, then the significant-digits frequencies of the combined sample will converge to the logarithmic distribution".* Gauvrit and Delahave (2011, p.16) reformulated the necessary conditions and argued that *"scatter and regularity are […] sufficient conditions for Benfordness"*. In a similar line of thought, Janvresse and De La Rue (2004) proposed that mixtures of uniform distributions lead to samples whose leading digits conform to Benford's law. Although, an interesting discussion on proving Benford's law holds (motivated by the fact that the set of positive natural integers sharing the same digit does not have a constant natural density) this chapter makes use only of the conclusions hereof in building an appropriate dataset. My dataset is constructed such that it complies with these necessary and sufficient conditions. As Durtschi *et al.* (2005, p.23) pointed out, failure to do so leads to the a-priory rejection of conformance to Benford's law.

In order to ensure scale/ base invariance, my dataset contains observations from 27 EU Member States and it reflects different processes – *i.e.* number of suspicion reports issued by the reporting entities, the efforts of law enforcement and the cross border movements of cash - over a period of eight years (from 2003 to 2010). I took the view of Michalski and Stoltz (2011) who argued that aggregating data from different processes over several countries should increase the likelihood that the dataset conforms to Benford's law. This is particularly relevant as missing data for some countries in my dataset, may not make these series

particularly representative for economic processes with exponential growth rates. Moreover, I expect that the scale of the efforts correlate to the scale of the financial sectors, to the scale of the GDP, therefore ensuring scale invariance. Moreover, the processes under investigation were various enough to ensure that data *"covers several orders of magnitude"* (Raimi, 1976) even when considering only national samples.

As the same time, Ettredge and Srivastava (1999) illustrated, ensuring that the dataset is correctly constructed does not ensure that non-Benford distributions immediately point to fraud. Data selection may still play a role, as well as operating inefficiencies. For instance, in theory, Benford's law applies to continuous random variables, a condition that is not met by datasets in general, but that can be remedied if datasets are sufficiently large. Following the reasoning of Michalski and Stoltz (2011, p.603), samples smaller than 110 observations have significant chances to produce type II errors (*i.e.* failing to reject a non-Benford's law distribution) which means that it is likely some of these samples do not follow Benford's law but we cannot reject the hypothesis they do. I have therefore employed Monte Carlo simulations in testing whether the data are conforming to Benford's distribution, using the method of Jann (2008). Moreover, Diekmann and Jann (2010) argued that before using Benford's law to uncover strategic behaviour, one must first prove that natural data follows Benford's law and that strategically modified data does not. Addressing their criticism, I took the view of Rauch *et al.* (2014) who argued that by using conditional probabilities, reference groups are created to judge the results observed in the test group. Additionally, I relied on the findings of Behavioural Economics which point, in numerous cases, to the fact that people perform poorly in probabilistic reasoning (*cf*. Tversky & Kahneman, 1971; Samuelson & Bazerman, 1985; Rubinstein& Tversky, 1993; Camerer, 2003). Finally, I agree with Durtschi *et al.* (2005) who cautioned that Benford's law alone cannot be used to claim having uncovered data fraud, but it can be useful if correctly interpreted.

5.2. Measures of goodness of fit to Benford's frequency distribution

I used several measures of distance between the empirical data and Benford's distribution, each accounting for different characteristics that the data and the samples may have had. Seeing how there are arguments to be made on more of these characteristics, I measured deviation from Benford's law with all available tools, and argued that, unless these characteristics played a major role, all these measures should have converged in revealing statistically significant deviances. The null hypothesis is that the first digits of the statistics on money laundering are drawn from Benford's distribution. I considered that the null hypothesis was rejected if the χ^2 test, the Kolmogorov-Smirnov and the modified Kuiper test, all, rejected it at 1%, 5% or 10% level.

The χ^2 goodness-of-fit test compares the empirical frequencies of the data under analysis $\widehat{\theta_j}$ with the frequencies of data following the distribution of Benford θ_j, [67]

$$\chi^2 = N \sum_{j=1}^{9} \frac{(\theta_j - \widehat{\theta_j})^2}{\theta_j}$$

where$N$ denotes the total number of observations. However, as Cho and Gaines (2007) pointed out, the χ^2 test has a particular drawback in its sensitivity to small samples. Michalski and Stoltz (2011, p.603) argued that given the limited degrees of freedom, the test is powerful for samples where $N > 110$. Since some of my samples were smaller than this (particularly when I redid the analysis on particular subsets), I made use of the multinomial-goodness-of-fit test introduced by Jann (2008), which sampled n units with replacement from a population of k elements of the Benford's law distribution. The number of replications for the sampling is 10,000. The exact p-value is equal to the fraction of replications in which the test statistic is at least as large as in the data under analysis (Jann, 2008).

The Kolmogorov-Smirnov test has higher power than the χ^2 test and is particularly appropriate for data having a natural order, which digits have. The test captures the highest absolute difference between the Benford's law and my observed, distribution function. Since the test is not meant for discrete data, I first transformed the data using the Monte Carlo method and then ran the Kolmogorov-Smirnov test (Jann, 2008, pp.160-166). I consider

$$KS = max_{1 \leq j \leq 9} \ [|H(j) - F(j)|], \text{ with}$$

$$H(j) = \frac{1}{n} \sum_{i=1}^{j} h_i \ \text{ and } \ F(j) = \frac{1}{n} \sum_{i=1}^{j} f_i \ ,$$

whereh_i and f_i are the observed and, respectively, Benford's counts for digit j (*cf.* Pettitt & Stephens, 1977).

The Kuiper test is a modified Kolmogorov-Smirnov goodness-of-fit test that recognizes both the ordinality and the circularity of the data on leading digits. The Kuiper test sums the maximum of the positive and of the negative deviations from Benford's law.

$$V_N = \max_{\mathrm{j}} \ [|\mathrm{H(j)} - \mathrm{F(j)}|] + \min_{\mathrm{j}} \ [|\mathrm{F(j)} - \mathrm{H(j)}|]$$

I adjusted the Kuiper test using Stephens' (1970) correction factor $V_N{}^* = V_N[\sqrt{N} + 0.155 + 0.24 \frac{1}{\sqrt{N}}]$ and made use of Morrow's (2010) critical values for $V_N{}^*$ (of approx 1.19 at 10%, 1.32 at 5%, and of 1.58 at 1%) which were shown to be asymptotically valid.

[67] Note that $j \neq i$ as one indexes countries and the other indexes samples, some of which containing cross-country data, as Section 6 shows.

In addition to the statistical tests, I included two measures of distance between the data under observation and Benford's distribution. These fall outside the hypothesis testing framework and are insensitive to the sample size. As suggested by Leemis, Schmeiser and Evans (2000), I calculated the distance measure $\mathrm{m} = \max_{i=1,\ldots,9}\{|\,(\theta_j - \widehat{\theta_j}|\}$. As suggested by Cho and Gaines (2007), I calculated the Euclidean distance between the two distributions, which I divided by the maximum possible distance (which would occur when all numbers begin with an FSD of 9) so that the value is bounded between zero and one: $\mathrm{d}^* = \frac{\sqrt{\Sigma_{j=1}^{9}(\theta_j - \widehat{\theta_j})^2}}{1.0363}$.

6. Results

It has already been explained how the dataset was constructed so that the necessary and sufficient conditions for it not to reject Benford's law by design were met. The methods presented in Section 5 can now be applied to test the predictions of my theoretical model. Hereafter, I only discuss the results yielded by sufficiently large samples that span across sufficient degrees of magnitude (*i.e.* $N > 110$ and $Scatter > 4$ in Tables 2-4). Finally, despite the fact that rejecting the null hypothesis is a potential sign of data manipulation, I prefer to analyze the relative probability of a sample being manipulated (*cf*. Durtschi *et al.*, 2005), in light of the incentive scheme discussed in Section 3. In doing so, I introduced a reference group and take out a potential tunnel vision that this analysis may otherwise have.

Proposition 1: All else equal, strategic manipulations of statistics will occur most when furthest away from evaluations.

Given the limited number of observations per country (Table A3.1), I needed to pool the statistics on money laundering across the 27 EU Member States, according to their distance relative to the evaluation moment.[68] For the same reason, I started three years before the mutual evaluation.

The 27 EU Member States were not evaluated at the same time. Instead, they were evaluated over a period of 5 years. This means that a comparison of data deviations across time, before countries were evaluated, is less likely to capture the effect of exogenous, not-related to money laundering related factors such as the financial crisis, changes in book keeping standards etc. If conducted at the beginning of the year, evaluators would only be able to take statistics of the previous year into account. In general, the report on the evaluation was published 6 to 9 months after the evaluation took place (exceptions were the Czech Republic

[68] The new variable 'MERp-4' pooled, for instance, all statistics (on repression, on suspicion reports and on cross border cash movements) that were published 4 years before the Mutual Evaluation of a country was published. They contained, among others, all the statistics for Germany in 2006, for Romania in 2004 and for the UK in 2003.

and Malta, which took more than 1 year before the report was published) (*cf*. FATF, 2009b). For indexing purposes, I considered the evaluation to be published one year after the evaluation takes place.

Furthermore, the FATF's *"Third Round of AML/CFT Mutual Evaluations - Process and Procedures"* guidelines proposed that countries should present a Follow-Up Report (FUR) two years after the publishing of the MER. Presenting the FUR in an FATF plenary session was comparable to publishing the results in an own evaluation. The country presenting had to report on the progress it had made since the mutual evaluation, particularly with respect to those recommendations where it received a partially compliant or a non-compliant qualification. Countries that had no such qualifications would not need to present a FUR, but no such example was present in my sample. In a FUR, great emphasis was placed on statistics, especially if they were found to be lacking in the mutual evaluation (FATF, 2009b, p.12). Due to bureaucratic delays,[69] the FUR usually contained statistics of the previous year and earlier statistics.

Figure 3.1 plots the deviations from Benford's law across time.[70] Deviation is captured using the different measures introduced in Section 5 – the Kuiper test, the Kolmogorov-Smirnov test, the χ^2 test (adjusted for sample size), the Euclidean distance (d^*) and m – the measure of Leemis *et al.* (2000). Figure 3.1 plots a succession of two evaluation cycles and shows that data deviate most, the furthest away the evaluation is. Evaluations take place at time MER and the results thereof are published the year after at FUR-1. The first cycle ends with an evaluation conducted by a group of external experts (*i.e.* MER) and the second cycle ends with the writing of an own evaluation (*i.e.* FUR) under the critical eye of the international community. Figure 3.1 points to large differences in deviation from Benford's law, before and after evaluations.

[69] FATF plenary meetings take place three times a year, in February/March, June/July or October/November, respectively. Countries need to send their FURs to the plenary in advance, as to allow for discussions (FATF, 2014).
[70] A check of conformance reveals that my entire dataset rejects Benfords' law at 1% (by K-S, $\chi^2$and Kuiper tests).

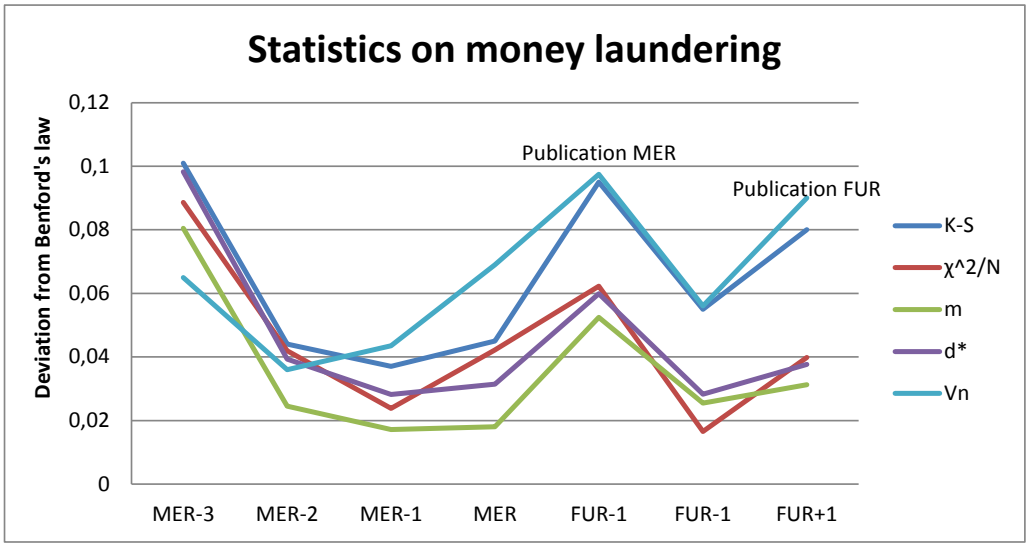

Figure 3.1: Timely assessment of conformity to Benford's law – statistics on money laundering. While in accordance with Table 3.3, for visual purposes the measures m and $d\mathrm{d}^*$ have been multiplied by a factor 10 and $V_N \mathrm{V_N}^*$ has been divided by a factor 20.

Equation 3.1 states that sending strategic private signals is more likely, the further away the evaluation is. Figure 3.1 shows that the highest deviation occurred three years before the mutual evaluation took place (at MER-3).[71] The same pattern is observed in the second round of international evaluations, as the highest deviation occurred the year before countries started writing the self-evaluation report (at FUR-1). Moreover, deviations are also significant at MER-3 in the first evaluation cycle, at FUR-1 in the second evaluation cycle, and at FUR+1 (Fig. 3.1).

Table 3.3: Assessment of conformity to Benford's law before and after international evaluations.

Variables[a]	N	χ^2	$K-S$	$V_N{}^*$	χ^2/N	m	d^*	*Scatter*
ML stats at MER-3	159	14.09*	0.101**	1.30*	0.09	0.008	0.010	4
ML stats at MER-2	264	11.08	0.044	0.72	0.04	0.002	0.004	9
ML stats at MER-1	318	7.57	0.037	0.87	0.02	0.002	0.003	10
ML stats at MER	349	14.74*	0.045	1.38**	0.04	0.002	0.003	10
ML stats at FUR-1	326	20.3***	0.095***	1.95***	0.06	0.005	0.006	10
ML stats at FUR	374	6.2	0.055*	1.12	0.02	0.003	0.003	9
ML stats at FUR+1	409	16.28**	0.08***	1.8***	0.04	0.003	0.004	9

Notes. [a] ML stats at MER-3, ML stats at MER-2, ML stats at MER-1 and ML stats at MER aggregate statistics on money laundering that were published 3,2 and 1 year before and

[71] Kuiper's test is the only distance measure to report differently in the first evaluation cycle.

respectively during the year of the international evaluation. ML stats at FUR-1 and ML stats at FUR aggregate the statistics published the year before and respectively during the compilation of the FUR. ML stats at FUR+1 aggregate statistics on money laundering that were published the year the FUR was published and discussed in the plenary. *p< .1, **p< .05, ***p< .01.

Table 3.3 reports, additionally, on two measures that confirm the appropriateness of using Benford's law to detect data irregularities, namely the sample size and the degree to which data is scattered. All of the samples used are sufficiently large ($N > 110$) and are sufficiently scattered (the data passes through at least four degrees of magnitude).[72]

Table A3.3 and Figure A3.1 reveal a similar analysis, performed on the three subsamples:[73] the data on the number of suspicion reports, the data on the efforts of law enforcement and the data on the cross border cash movements. With this analysis I have checked which components drove the results presented in Table 3.3. The results did not hold for the subsample cross-border cash movements, but this subsample was also not sufficiently large for the use of Benford's law. The other subsamples were given, and there Proposition 1 was also confirmed.

Proposition 2:All else equal, in the aftermath of an international evaluation, statistics of money laundering of countries that receive a negative evaluation deviate more from Benford's law than those of countries that received a positive evaluation.

In order to test this, I grouped countries into four categories ranked 1 (best conforming) to 4 (least conforming) according to their FATF/ Moneyval evaluations on recommendations 13, 16, 27, 31 and 32. I selected only statistics recorded after the mutual evaluation took place, and therefore aim to capture the effect of the mutual evaluation on deviations in the second evaluation cycle. Ideally, I would have liked to make use of national data, but as Table A3.1 shows, country data is too scarce to allow for comparison when taken over the entire time period 2003-2010, especially only after the mutual evaluation has taken place. Furthermore, seeing how strategic manipulations of cross-border cash movements are more difficult to implement, I only pooled data on law enforcement's repression efforts and data on the number of suspicion reports for testing this proposition.[74]

In Group 1, I aggregated statistics of countries that have been rated C or LC, and only on maximally one account PC on recommendations 13, 16, 27, 31 and 32. In Group 2, I pooled statistics of countries that performed less well, in the sense that their panoply of good evaluations was spoiled only on two accounts with a PC, or on one account with a NC. In

[72] Samples {1, 20, 100, 1001} and {100, 2007, 19900} cross, for instance, 3 degrees of magnitude.
[73] Though the name is suggestive, Table A3.2 shows precisely which variables compose each of these subsamples.
[74] Table A3.3 and Table A3.4 show that data on cross-border cash movements does not follow Propositions 1 and 2.

Group 3, I aggregated statistics of countries that were being rated on three accounts with PC or on two accounts – once PC once NC. Finally, in Group 4, I pooled data of countries that were evaluated by the international community with PC or NC on most if not all accounts.

Proposition 2 suggests that deviations from Benford's law occur most in the 2nd, 3rd and 4th group. Table 3.4 reports the divergence of these four groups from Benford's law. The group pooling statistics of the better rated countries did not significantly deviate from Benford's law, while the rest did. Table 3.4 shows that the groups did not prompt the rejection of Benford's law by design: the samples were sufficiently scattered and large. This evidence supports the hypothesis that evaluations results induce strategic manipulation of statistics by countries.

Table 3.4: Assessment of conformity to Benford's law – statistics on law enforcement's repression efforts and on the reporting entities' signalling efforts, published after the international evaluation took place.

Groups	N	χ^2	KS	V_N^*	χ^2/N	m	d^*	*Scatter*
1: BE, EE, NL, UK	158	3.86	0.051	0.65	0.02	0.002	0.004	5
2: CY, CZ, ES, FI, HU, IE, MT, PT, LV	552	27.87***	0.072***	1.86***	0.05	0.003	0.003	4
3: AT, BG, DK, FR, IT, RO, SE, SL	379	15.8**	0.066**	1.29*	0.04	0.004	0.004	4
4: DE, EL, LT, LU, PL, SK	212	22.22***	0.133***	2.13***	0.10	0.009	0.010	4

Legend: **p< .1, **p< .05, ***p< .01.*

Proposition 3: If, as a result of a round of mutual evaluations, more countries are negatively evaluated, all else equal, aggregate statistics on money laundering will deviate more from Benford's law in the aftermath of the round of mutual evaluations than before.

Proposition 3 derives from Propositions 1 and 2 and states that, in the aftermath of a round of mutual evaluations, where most countries are negatively evaluated, statistics on money laundering will be less reliable than before the evaluation. Derived in the Appendix, Equation 3.3 states that if sufficiently many countries are negatively evaluated ($x \geq x_{min}$), the aggregate optimal level of data manipulation is higher in the aftermath of the round of mutual evaluations than before. Table 3.1 shows that, for 5 out of the 40+9 Recommendations, just two member states (Belgium and the United Kingdom) received only positive evaluations.

Table 3.5 reports on testing the Proposition 3 on aggregate statistics (repression data, suspicion reports data and cross-border cash movement data) and shows that statistics did not significantly deviate from Benford's distribution before the publication of the MER, but significantly deviated after the evaluation. The samples used to test Proposition 3 are both sufficiently large and scattered to ensure the validity of the results. Table A3.5 reports on the

application of the same method on three subsamples: data on suspicion reports, data on cross-border cash movements, and repression data. With the exception of the statistics on cross-border cash movements, Proposition 3 is confirmed in the subsamples as well.

Table 3.5: Assessment of conformity to Benford's law: aggregate statistics before and after the publication of the MER.

Variables	N	χ^2	KS	$V_N{}^*$	χ^2/N	m	d^*	*Scatter*
ML stats before MER publication	1281	12.42	0.024	1.07	0.01	0.001	0.001	10
ML stats since MER publication	1873	34.81***	0.056***	2.54***	0.02	0.001	0.001	10

Legend: *Statistics marked 'before MER publication' aggregate data from 2003 until the year before the MER was published; statistics marker 'since MER publication' aggregate data from the moment the evaluation is published until 2010; *p< .1, **p< .05, ***p< .01.*

Alternative explanations and limitations

In previous sections, I discussed whether countries deviate more from Benford's law when exposed to the pressures from the international community. A fundamental assumption that underpins this chapter is that deviations from Benford's law can, in fact, point out unreliable data. To avoid the problems that Durtschi *et al.* (2005) described, as Rauch *et al.* (2011), Rauch *et al.* (2014) and Michalski and Stoltz (2011), I made use of conditional probabilities when applying Benford's law to unmask unreliable data. Nevertheless, Benford's law could not, on its own, tell anything about whether this unreliability was due to strategic behaviour, and it could not determine which organizations tampered with the statistics. Given the data limitation, I could not differentiate among the organizations providing the statistics and instead, referred to countries possibly engaging in strategic reporting.

Moreover, alternative explanations for unreliable data have been put forward. These explanations are still based on the assumption that deviations from Benford's law are a measure of the degree of the unreliability of the data, but distance themselves from strategic tampering/ fraud etc. Holz (2003) and Judge and Schechter (2009) argued that developing countries may have unreliable statistics not because of fraud but because of procedural problems, lack of resources and faulty calculations. Although collecting statistics on money laundering is a novel international enterprise as opposed to, for instance, having national balance of payments statistics or fiscal deficit statistics, none of the EU Member States between 2003 and 2010, could be labelled *'developing countries'*. Additionally, Judge and Schechter (2009) argued that respondents to surveys were in general inclined to fill in round-sum numbers where answers were vague. In the case of official statistics on money

laundering, I suspect approximations were not aimed for, despite the fact that the FATF guidelines do not require accuracy in particular.[75]

Finally, Table A3.1 shows that Finland, Germany and Spain published almost twice as many statistics on money laundering than Greece and Poland. Additionally, Kristen argued that law enforcement agencies may simply not consider statistics a priority in the context of the AML efforts (*cf*. ECOLEF, 2013). Missing data can impact the probability distribution of first digits. This is essentially problematic when using Benford's law because it poses the question: do countries cheat by tampering with statistics or by providing no statistics? In the event that Benford's law becomes part of the standard data checking mechanisms, it should therefore be reinforced by the more stringent requirement that data be collected and published, if it is to be effective.

7. Conclusion and policy recommendations

In this chapter, I have posed questions and subsequently provided answers. In light of the method I employed, this was to be expected. The question – what do violations of Benford's law really mean – is *"an epistemological question that underlies all applications of Benford's law"* (Nye &Moul, 2007, p.10). Although it does not guarantee (malevolent) human error, Section 2 showed that it is, in fact, a well-established alarm signal, familiar to several disciplines. Without a theoretical explanation of non-conformity, this chapter would stop at the question and at most only cast doubts about the accurateness of the official EU statistics on money laundering. Instead, with the help of a stylized model of incomplete information, I represented the incentives to tamper with statistics induced by international pressures and raised awareness on the likeliness that countries may tamper with their statistics, especially after being criticized by the international community.

The central question of this chapter is: do countries strategically manipulate their statistics in response to international pressures forcing them to dedicate resources to combating money laundering? The answer is: *from a statistical point of view, yes*. In order to answer this question, I have built a convenient dataset that did not reject Benford's law – *i.e.* answering yes – by design. This is an exception, in the context of the recent social science literature (Section 2) that uses Benford's law, where samples were generally insufficiently large and insufficiently scattered, and did not mimic random samples taken from several sequences of natural numbers. My dataset contained yearly statistics for 27 EU Member States from 2003-2010 on, among others, the number of suspicion reports issued by national reporting entities, on the number of investigations, prosecutions and convictions for money laundering

[75] *"Competent authorities should maintain comprehensive statistics on matters relevant to the effectiveness and efficiency of systems for combating money laundering and terrorist financing"* (FATF, 2009a, p.38).

undertaken by the national law enforcement agencies and on the cross border cash movements overseen by the national agencies. I employed several measures of divergence to test whether the distribution of first digits of my samples were significantly different from Benford's law. These measures accounted for different characteristics that data under investigation may have, and despite these implicit differences, they all corroborated my hypotheses.

Strategic manipulations of statistics, as I have presented, are not unheard of, and could be expected even in the case of countries. The sole observation that statistics diverge from Benford's law cannot reach out to the source of the data's unreliability and may additionally trap the researcher into a certain tunnel vision. In this chapter, I developed a stylized model of signalling under imperfect information and hypothesized about the circumstances under which strategic behaviour would most likely occur. Conversely, I addressed the latter issue by comparing the deviations from Benford's law, of samples where strategic manipulations of statistics were, theoretically, more likely to occur, with samples where strategic manipulations were less likely to occur. My data confirmed that strategic manipulations of statistics on money laundering occurred the further away international evaluations were. Deviations from Benford's law were, therefore, highest and most significant, irrespective of the measure of deviation chosen, the further away the evaluations were. Furthermore, I showed that statistics on money laundering significantly diverged in the aftermath of the round of Mutual Evaluations conducted by the FATF and by Moneyval, whereas they did not *ex-ante*. Finally, I showed that countries that were negatively evaluated on their efforts by the international community exhibited higher ex-post strategic manipulations than countries that were positively evaluated. Groups of countries that were poorly evaluated had therefore, ex-post high and significant deviations from Benford's law, whereas the group of countries that were positively evaluated presented statistics that did not significantly deviate from Benford's law ex-post.

Importantly, on the policy side, my analysis revealed that, according to Benford's law, the moment that Member States started being evaluated on the basis of their statistics, EU statistics on money laundering became more unreliable and presented evidence that the patterns of deviation from Benford's law were in line with patterns of strategic reaction to the pressures of the international community. The fact that Member States engaged in strategic manipulation of their statistics on money laundering, thereby effectively exploiting the information asymmetry between them and the international community is problematic as it makes statistics unreliable for the purpose of both policymaking and research. Knowing this, are regular evaluations optimal from a welfare point of view? Or will the presence of evaluations just drive the verge between statistics and reality? I showed that once evaluated, country statistics deviated from Benford's law every time countries were not evaluated, and even more after negative evaluations. The solutions, I argue, are imperfect and deserve

further analysis: 1) maintain current country comparisons and add Benford's law to the existing set of data checking methods; 2) have countries *permanently* monitor each other; or 3) avoid country comparison altogether. My work complements that of Masciandaro and Portolano (2004) who argued that when the international legal community cannot perfectly screen countries with lax financial regulation, blacklisting is not wise, as it markets the blacklisted country to the criminal community as a supplier of money laundering services.

Benabou and Laroque (1982) argued that in models with imperfect information, in the presence of cheap talk, gurus will still transmit information when signalling, even if not about the state of the world, but about their true intentions. Following such a guru over time may be rational if only to discover if they are a strategic manipulator. Knowing that the FATF standards have just been readjusted (FATF, 2013) and that this will translate into new pressures for countries to once again conform, I argue that the scenarios studied in this chapter will likely repeat. One advice for policy makers that requires least institutional change is that future statistics be checked against Benford's law on a regular basis and that alternative methods to create true compliance and to evaluate a country's true efforts to combat money laundering are enforced as well. Nevertheless, if we believe that economics is a reflexive science (Soros, 1987), this solution is not long termed, as markets will learn of today's novel method thereby making its application for the purpose of uncovering data manipulations obsolete.

Alternatively, since the source of unreliability is information asymmetry driven signalling, one policy making advice is to target the information asymmetry. Evaluating countries on a yearly basis may reduce the information asymmetry and statistics could therefore, be expected to better match reality. This proposed solution, however, is the most resource intensive one. The costs associated with maintaining such a high level of international coordination are certainly very high, and thus, this solution is less feasible. With high operating costs for fighting money laundering[76] and with unreliable statistics to back up the effectiveness of the employed methods, one may wonder if setting even higher standards of compliance (*i.e.* the extension of enhanced due diligence for politically exposed persons, the better monitoring of the gambling sector and the specific mentioning of tax crimes in the list predicate offences for money laundering that are contained in the 4th EU Anti-Money Laundering Directive) without effectively imposing checks on the validity of statistics, is not just an inertia driven measure meant to justify the involvement of policy makers for the well-functioning of the market in area of defence. And should we not then instead question the rationale to impose, in the first place, a market framework to the governance of national defence? Taking the view of Becker (1973) and of De Fleur (1975), crime data can be seen as the intersection of three Venn diagrams – one illustrating the size of the criminal sector, one illustrating the efforts of law

[76] ECOLEF (2013) estimated yearly ongoing costs of fighting money laundering to be approximately 44mln Euro for a hypothetical country with a population of about 10 million, with an average exposure to the financial crime.

enforcement to combat it and a third one illustrating the desire of society to fight crime. Crime data should not be used as proxy for any of the three as this excludes the other two forces, and therefore country comparison on this basis should be avoided altogether. Moreover, if evaluations do not happen yearly, strategic reporting will occur in- between evaluations at the shelter of asymmetric information and the optimal policy response is therefore, once again, avoiding country comparison on the basis of crime statistics. Although relatively cheap, from a policy point of view, this solution offers even more challenges – as it discards a currently faulty system without offering a better alternative.

Chapter 4 – What drives BITCOIN investment: legal, financial, or technological opportunities?

This study is co-authored with Radu Serban and Brigitte Unger.

1. Introduction

In 2008 the world was taken by surprise by a new concept – a new form of money called BITCOIN. Anticipated by the IT community and awaited by libertarian ideologists, BITCOIN's popularity among economists lies in its capacity to solve the fundamental problem of exchange without intermediaries. In a potentially irreversible paradigm shift, BITCOIN proponents suggested trusting publicly available algorithms instead of well-known financial intermediaries: the banks (*cf.* Nakamoto, 2008). The multi-facets of this paradigm shift – *i.e.* a higher degree of anonymity, systemic transparency, low transaction costs – next to the novelty induced instability and regulatory ambiguity, have almost immediately triggered opportunistic and frightening thoughts and emotions among the general public and regulators alike. Furthermore, only few of the questions raised by BITCOINs have been answered so far. Consequently, research into crypto-currencies is needed and, at the same time, promises to be a rich and fruitful field to tap into.

In this chapter, we examined how online information referring to BITCOINs influenced transactions volumes and the Dollar-to-BITCOIN exchange rate. We used computational linguistics to analyze 13,287 articles that Google returns on daily "BITCOIN" queries, to construct new measures of the composition and evolution of investor attention to the BITCOIN discourse. These measures reflected investor attention to the legal, financial and technological threats and opportunities of BITCOINs. We used these new text-based measures to test hypotheses about the behaviour of BITCOIN investors and, simultaneously, to distinguish different BITCOIN user groups as well as their main sources of information.

Our focus on the threats and opportunities underlying the BITCOIN discourse to explain transaction volumes and prices was motivated by a few recent theoretical exercises. After reviewing the statements of Warren Buffet, Alan Greenspan, Paul Krugman and the Winklevoss brothers, Investopedia concluded *"BITCOIN has value because people think it has value"*.[77] Arguing that the BITCOIN discourse is what drives investors' valuations, Maurer,

[77] The Easy Way To Measure Bitcoin's Fair Market Value: A Do-It-Yourself Guide (Investopedia) (retrieved from

Nelms and Swartz (2013) suggested that financial considerations are not uniquely important. Instead, they argued that the value of BITCOINs does not depend on *"whether Bitcoin works as a currency, but [on] what it promises: solidity, materiality, stability, anonymity, and, strangely, community."* Indeed, in the literature review, we distinguished three recurring themes in the BITCOIN discourse: a financial, a legal and a technological theme.

In constructing new measures of investor attention, we started from the discourse on BITCOINs that Google returns to queries on "BITCOIN". At the basis of our computational linguistics laid grounded theory (Glaser & Strauss, 1967; Corbin & Strauss, 1990), and the qualitative data analysis methods of Miles and Huberman (1994), that were adapted to account for automated data analysis. The measures generated represent, in fact, the number of weekly new texts discussing legal, financial or technological threats and opportunities in relation to BITCOINs, which Google returned to (potential) investors querying on "BITCOIN". The measures of information we distilled from the BITCOIN discourse were informative on the discussion topic (*i.e.* law, finance or technology) but not on the sentiment of the information (*i.e.* whether it reflected threats or opportunities). For instance, the apprehension of Ross Ulbright – founder of Silk Road – by the Federal Bureau of Investigation (FBI) triggered a great volume of legal information. However, the discourse was mixed on what this meant for anonymity: for criminals it was seen as a threat, and for legitimate businesses using BITCOINs it was an opportunity to attract legitimate customers.

In other words, our measures of information may reflect both threats and opportunities for BITCOIN investors. We therefore expect these measures to influence the volume of transactions more than prices. We expect that transaction volumes and prices are stable in the absence of new discussions on the financial, legal or technological threats and opportunities induced by BITCOINs. Alternatively, and in line with the literature on investor attention (*Cf*. Ross, 1976; Merton, 1973), if new information reflects opportunities (threats) then prices increase (decrease) by incorporating this information. However, if information reflects both opportunities and threats, then prices cannot be used to measure investment attention, but transaction volumes should increase when investors incorporate this information, and should indicate the adjustment of BITCOIN trading activity (*Cf*. Glaser, Kai, Haferkorn, Weber& Sieiring, 2014).

The central finding of this chapter is that BITCOIN investors trading on financial markets reacted to financial and technological information published on BITCOINs by adjusting their trading activity. Since our measure of financial and technological information was not sensitive to sentiment, prices reacted only to new financial information and to a lesser extent than transaction volumes. Furthermore, BITCOIN investors that mostly transacted in BITCOINs

www.investopedia.com/articles/investing/050914/easy-way-measure-bitcoins-fair-market-value-doityourself-guide.asp)

(*i.e.* outside stock exchanges thus) reacted only to legal information, again by adjusting their transaction activity accordingly. This suggested that while traders on the stock exchange were interested in BITCOIN speculation, BITCOIN owners that transacted for goods and services outside the stock exchanges were interested in the legal/ illegal component of BITCOINs. Finally, our analysis suggested that information published on websites with a dedicated financial and technological profile, in the news and in forums had the highest impact on financial markets, whereas, information coming from blogs and news articles had the highest impact on non-financial markets.

Our study is the first to illustrate the extent to which particular themes of the BITCOIN discourse were picked up by BITCOIN investors and influenced their transacting and trading activity. Although our measures of information did not distinguish between the often contradictory discussions on the properties of BITCOINs (*cf*. Grinberg, 2011; Lane, 2014; Kaplanov, 2012), they distinguished the theme of the discourse.

This chapter also adds to the understanding of what drives investment into BITCOINs and builds on the works of Kristoufek (2013, 2014), Buchholz, Delaney and Warren (2012), Glaser *et al.* (2014) and Yelowitz and Wilson (2015). The information measures that we constructed are more transparent and richer than the measures for investor attention employed by the former two – *i.e.* Google and Wikipedia trends. They, therefore, allow us to examine several insights from Glaser *et al*, Yelowitz and Wilson – namely that different groups, interests and ideas coexist and drive the BITCOIN market.

We also contributed to the growing literature on investor attention (Peng, Xiong & Bollerslev, 2007; Gabaix, Laibson, Moloche & Weinberg, 2006; Sims, 2003) which shows that, investors who have limited attention prioritize particular pieces of information. Furthermore, we showed that when measures of information were not sentiment sensitive, transaction volumes were more likely to capture changes in the measures of information than prices, since information may have reflected both threats and opportunities given the particular nature of the investors and their beliefs.

Importantly, with this research, we showed that it is possible to capture some of the basic interests behind the BITCOIN market, even in the presence of anonymity. We further showed that it is possible to identify the key signal givers for the BITCOIN market, as well as the impact of their signals on market participants. Notably, in this chapter, we emphasized the relevance of developing new and richer measures for investor attention. Google trends and Wikipedia trends have so far supported the development of a growing literature to which this chapter adheres. Understanding and predicting behaviour by analyzing collateral data has long materialized (*cf.* Boyd & Crawford, 2012; Kosinskia, Stillwella & Graepelb, 2013). Armed with higher computing power, better filtering algorithms and a better understanding of what

the BITCOIN users discuss, we can replace the Google and Wikipedia trends – two measures lacking specificity and clarity – with more accurate and transparent measures.

The remainder of this chapter is organized as follows. Section 2 summarizes the discussion on BITCOINs from 2009 to present and reviews earlier attempts to explain price and transaction movements in the BITCOIN market. In section 3 we develop and motivate the testable hypotheses. Section 4 discusses our data and methodology. Section 5 introduces the text-based measures of investor attention and provides examples and descriptive statistics that facilitate interpretation. Section 6 presents the main empirical results, and Section 7 concludes.

2. Literature review

The literature on BITCOINs can be divided into three strands: descriptive, exploratory and explanatory. Given the novelty of BITCOINs, the lack of **regulation** and the associated risks thereof for both businesses and governmental bodies (*Cf*. Brito & Castillo, 2013, p.2), it is not surprising that the first strand is most developed.

From the descriptive literature (Grinberg, 2011; European Central Bank (ECB), 2012; Brito & Castillo, 2013) as well as from their forerunner blogs and forums (WeUseCoins.com; Motherboard; Wikipedia; Investopedia), including the seminal paper of Nakamoto (2008), we know that BITCOIN is a decentralized digital currency[78] that is, for the first time, able to solve the "double coincidence of wants" without having to rely on a trusted third-party intermediary (Buchholz, Delaney & Warren, 2012). Instead, in the BITCOIN network, double spending is avoided by design, as transactions are only validated once they are public information to the BITCOIN users (*cf.* Nakamoto, 2008). In other words, the transaction takes after it is 'gossiped to' other users and once it is logged into the blockchain – *i.e.* BITCOIN's public ledger.

Most of the descriptive literature on BITCOINs focuses on giving a clear picture of how BITCOIN works (*cf*. Grinberg, 2011; Brito & Castillo, 2013; Bryans, 2014, pp. 445-447; ECB, 2012, in order of complexity). In short, users are given two keys, one which is private and one that can be made public. As BITCOIN user, when I wish to send BITCOINs to you, I need to know your public key. My computer then sends a message to the other BITCOIN users that I am using my private key to sign BITCOINs from my own wallet to your public key. Upon transfer, the message of my transaction to you will be recorded in a public ledger that, in

[78] The internet offers a wide array of digitalized currencies. While bearing different names, most are identical in algorithm. Among the main different ones there are BITCOINs, LITECOINs, ZEROCOINs (*cf.* Wikipedia, https://en.wikipedia.org/wiki/List_of_cryptocurrencies). The circulation of BITCOINs was highest in the period we analyse in this chapter.

principle, is time irreversible (*Cf*. Kroll, Davey & Felten, 2013)) and permanent. As Paar, Pelzl and Preneel (2010) described, public-key cryptography, the basis of the BITCOIN transaction protocol, is energy intensive as logging transactions in the public ledger demands a great deal of computing power. Without users that log transactions onto the public ledger, the distribution of information – the crucial solution to the fundamental problem of exchange – could not take place. Therefore, users that log transactions are compensated for their efforts – by algorithmic design – with newly created BITCOINs. Since, users that log transactions are in fact doing it for the purpose of acquiring new coins, they are called miners.

In a BITCOIN primer, Maurer *et al.* (2013) discussed the social semiotics of BITCOINs. By tapping into the conversations on BITCOINs, the authors distilled what fundamentally troubled and incited individuals thinking about BITCOINs.[79] The authors argued that the choice in symbols and allegories to characterize BITCOINs seemed not random. Rather, it was based on deeply socially rooted philosophical discussions on the nature of money, credit and capital in the modern world. As such, they argued that BITCOIN's semiotics should be understood as practical materiality expressed via a digital metallism. In the author's view, "the point is not whether BITCOIN works as a currency, but what it promises: solidity, materiality, stability, anonymity, and, strangely, community." Moreover, and very important, it is these promises that incite users and the debate on them promises to be a long lasting one (Maurer *et al.*, 2013). The paradigm change introduced by BTICOINs has, in fact, also introduced many concerns and opportunities. *"BITCOIN's image within the US is polarized. Some view it as a tool used by criminals to commit crimes, whereas others view it as a tool for a legal system of currency that is free from unlawful government interference"* (Bryans, 2014, p. 448). In our view, the threats and opportunities discussed in the academic literature, discussed by members of the BITCOIN community, presented in the media and advertised by businesses, can be split according to their substance in three categories: legal, financial and technical.

2.1. Legal threats and opportunities

Made for criminals? The legal threats and opportunities relate to the potential use of BITCOINs by **criminals**[80], in particular due to their unclear **legal status** and to their (full) **anonymity**. The unclear legal status relates to the formal monopoly that governments had over the money supply. Can BITCOINs be a new form of money and would this competition be forbidden? Can BITCOINs fraudulently be identified with national currencies? Are they commodities that should be regulated as such (Plassaras, 2013)? Who should tax them and is it possible that they are taxed? All these legal questions are discussed in the context of the US

[79] We believe their paper reflected first the opinions of BITCOIN lovers and how these were forecasted to arouse interest. The authors nevertheless were silent on the efforts undertaken by BITCOIN contenders, although those may have also been many.

[80] For visual purposes, we emphasized in the literature review the themes and codes used to classify the BITCOIN corpus. Section 5 describes the functional and the semantic classification methods we employed.

legislation by Grinberg (2011), Dion (2013) and Bryans (2014). Conversely, if the legalistic discussion was easily consumed, at least in the case of the US, the practical discussion on the nature of anonymity allowed by BITCOINs is by far not settled. Furthermore, if not taxed, will it become the next major **tax** haven (*Cf*. Turpin, 2014; Trautman, 2014)?

With respect to anonymity, the debate is placed in wider debate on the need for financial transparency. Proponents of privacy argued that privacy desires can have many legitimate reasons, such as avoiding abuses and discriminatory reactions from family members, employers or others (Brito & Castillo, 2013, p.15). Conversely, law enforcement agencies focused on the money laundering risks associated with anonymity. Bryans (2014) and the FBI (2012, p.5) presented and discussed some common knowledge mechanisms to ensure anonymity in the BITCOIN network, and argued that BITCOIN users could easily make mistakes that could give away their anonymity. Reid and Harrigan (2011) and Androulaki, Karame, Roeschlin, Scherer and Capkun (2013) actually showed that by studying transaction patterns of individuals given the records in the **block**-chain they could find out significant information about the real world identity of those users. In other words, behaviour based clustering techniques are believed to reveal vital clues about the true identity of the transferring parties. Nevertheless, their analysis did not prove that behaviour based clustering techniques can reveal vital information about all participants in the BITCOIN network, thereby constituting a real threat to the criminals therein. Consequently, the FBI (2012, p.2) recognized BITCOINs as a tool that can be used by criminals to *"generate, transfer, launder and steal illicit funds"* given its anonymity. Moreover, the FBI (2012, p.10) recognized that the more widespread BITCOINs become, the better the tool they make for criminal purposes.

Resembling previous fraudulent financial vehicles: BITCOIN has been compared with **Liberty** Reserve (Cochan, 2013), a company owned digital currency service that allegedly was used for money **laundering** (Santora, Rashbaum & Perlroth, 2013). Owing to a **Federal** crackdown on Liberty Reserve, BITCOIN adversaries suggested a similar measure towards BITCOINs since they too lacked transparency and promised anonymity (Cochan, 2013). BITCOIN proponents nevertheless counteracted by saying that the **peer-to-peer** system induces full transactional transparency, and that in fact it may be very costly for money launderers to hide their true identity (*cf*. Brito & Castillo, 2013). Further, BITCOINs have also been compared to cash and E-gold, as an anonymous means of transfer that is known to be preferred by criminals to bank accounts for money laundering (Villasenor, Monk & Bronk, 2011). The comparison was interesting, as on the one hand, E-gold creators were charged with money laundering and facilitation of crime (*cf*. Turpin, 2014), and on the other "policymakers would never seriously consider banning cash" in the view of many academic, including Brito and Castillo (2012). In fact, **policymakers** in Italy and in the UK have taken several measures already to limit the usage of cash (Migliaccio and Sirletti, 2011) and the ease of transfer respectively (Casciani, 2010). Consequently, attempts could be made to limit the usage of BITCOINs.

Disguising financial transactions and hiding them from the vigilant eye of governments do not require sophisticated IT solutions. The informal value transfer system Hawala was long used in the Middle East North African regions to facilitate cross border transactions with minimal real **traces**. As Villasenor *et al.* (2011) argued, modern technologies, including digital currencies, such as BITCOIN, add endless possibilities to increase financial opacity. However, Villasenor *et al.* (2011) also pointed out that BITCOIN was not the only major game changer in the field of payment systems since the beginning of the millennium. African developed mobile money transfer system M-PESA offered equally many applications for disguising illicit financial transactions, and it was simply the turn of cyber-crime **fighters** and regulators to respond to these new challenges. Moreover, Villasenor *et al.* (2011, p.14) reminded us that "measurement of financial activity, whether at the macro level in terms of GDP or at the micro level in terms of specific transactions, has always been a difficult and highly error-prone exercise".

Evidence of successful use for criminal purposes: The criminal reputation of BITCOINs is allegedly owed to the association with known criminals. In a fascinating study on the functioning of Silk Road, Christin (2012) argued that BITCOINs used for criminal purposes are only worth 1.2 million dollars (0.15% of total BITCOIN value) and concluded that one cannot speak of significant usage of BITCOINs for criminal purposes.[81] For this reason, some US **politicians** even accepted contributions in BITCOINs to their political campaigns (Bryans, 2014, p.450). Conversely, a letter of two other US Senators towards the US Attorney General Eric Holder asked for the criminal follow-up of BITCOINs, the currency allegedly core to the Deep Web black market Silk Road, and to many hacker demanded rewards (Bryans, 2014, p.448). Their belief was that, in the hands of savvy IT users, knowledgeable of IP protection techniques and of the use of The Onion Router [TOR] networks, a higher degree of anonymity could be achieved that would effectively shield criminals from law enforcement (*cf*. Turpin, 2014, pp.358-359). The FBI (2012) gave examples of known cyber criminals accepting payments only in BITCOIN, Webmoney, and Liberty Reserve for **botnet** services; and of criminal organizations laundering money with the help of BITCOINs, through virtual games. On the contrary, proponents of BITCOINs argued that anonymity served as shelter to onerous **donations** made by law abiding individuals who supported counter-governmental groups such as Wikileaks, or even hacker groups such as LulzSec (*Cf*. Brito & Castillo, 2013).

Non-regulated entry and exit points: During the US Congressional hearings on regulating virtual currencies Hugues suggested that providers of virtual currencies as any other economic operators had to comply with the USA Patriot Act (Trautman, 2014, p.36). However, according to the FBI (2012), decentralized digital currency systems are "*incapable of conducting due diligence, monitoring and reporting suspicious activity, running an anti-money*

[81] The study estimated only the amounts of BITCOINs used in Silk Road transactions and can therefore at best offer a minimum static threshold to the BITCOIN related criminal activities.

laundering compliance program, or accepting and processing legal requests like subpoenas". As a result, criminals could introduce illicitly obtained gains into the BITCOIN ecosystem and take it out as clean cash. Bryans (2014, p.447) argued that the lack of paper trail for investigators to follow in fighting crime made **law enforcement agencies** face even more difficulties than before: *"Bitcoin and analogous virtual currencies could enable money launderers to move illicit **funds** faster, cheaper, and more discretely than ever before"*. Especially as BITCOIN exchange services were registered all across the world, additional anonymity may be offered to criminals in laxer regulatory **jurisdictions** (FBI, 2012). Moreover, as Villasenor *et al.* (2011) pointed out, BITCOIN and randomizing systems made smurfing in BITCOINs much more effective than before. With lacking regulation on the exit and entry points, endless possibilities to avoid leaving paper trails for **investigators** and governments to track money, **AUSTRAC**, the Australian Financial Intelligence Unit (FIU) argued that BITCOINs fall outside global AML legislation and that it could be a useful tools for criminals. Nevertheless, the report did not criminalize BITCOINs, and just as the FBI (2012) report, it suggested that the market for BITCOINs was too small and its acceptance too limited to consider it a serious threat to global AML efforts (AUSTRAC, 2012). Consequently, Brito and Castillo (2013, p.9) argued that once BITCOIN intermediaries complied with AML regulation, it would be even more difficult to maintain anonymity when transacting in BITCOINs, since these intermediaries would need to comply with the customer due diligence requirements.

Recommendations however to regulate exit and entry points have so far been scarce, as regulation may drive out good investments and force the market of BITCOINs to collapse, while criminals always find a way to launder their ill-gotten gains (Brito & Castillo, 2013, p.22). As Unger and Den Hertog (2012) previously proposed, regulation will not stop criminals from laundering, but may, in fact, just support them to substitute one financial tool for another. Instead they argued for smart regulation, if any: one that reduces asymmetric information between criminals and regulators, allows law enforcement agencies to target ill-gotten gains and allows legitimate users to benefit from these novel financial constructions without their actions further being monitored and exploited.

Non-reversible transactions: BITCOIN transfers are not reversible, a property much appreciated by small businesses that depend on exports. With no-reversible transfers, the costs associated with charge-back fraud decrease for small exporting businesses. Conversely, buyers may see this as a threat since they run the additional threat of being cheated by abusive businesses. As a result, BITCOINs and credit card payments will co-exist, in order to cater for different degrees of risk taking **buyers** (Grinberg, 2011).

Contesters of BITCOINs – and especially law enforcement authorities warn against the risks associated with the effective investigation, **prosecution** and criminal **forfeiture** when assets are kept in BITCOINs (Lane, 2014). Next to the fact that anonymity impedes severely the

capacity of law enforcement to construct probable cause in order to search or seize suspected E-wallets, PCs etc., the time delays imposed by these requirements may make searches ultimately useless, as probable cause may be developed after suspects transferred their assets elsewhere (Lane, 2014, pp.540-542). Conversely, proponents argued that when governments abusively nationalize private assets, where hyperinflation destroys private property (see exposition Turpin (2014) on **Cyprus** and Iran), BITCOINs can actually support onerous property owners.

2.2. Financial opportunities and threats

Competitive transaction costs: One of the earliest proposed advantages to BITCOINs was its **competitive transaction costs**, with some websites advertising even 'no transaction costs' to international transactions (Zielke, 2011). The straightforward implications thereof included the lowering of costs for businesses transacting abroad (a threat to the existing Money Gram and Western Union money wire services), alleviating **poverty** in social groups which depend on global **remittances** (*i.e.* Hawala systems), and increasing access to **capital** for micro-financed entrepreneurs in countries with no **financial** infrastructure, in the same way M-PESA did (Jack & Suri, 2011). And while BitPay seized this opportunity (Simonite, 2013), **credit** card companies complained that this was not a **regulatory** level playing field, since BITCOIN operators did not need to comply with costly KYC regulations.

A concern voiced by some businesses, who expressly do not accept BITCOINs (Wikimedia) or who no longer accept BITCOINs (the Electronic Frontier Foundation) is related to their 'potentially criminal' nature (Bryans, 2014, p. 454). Finally, Turpin (2014) interestingly applied the findings of Gu and Hitt (2001) to the market for BITCOINs. Gu and Hitt (2001) showed that reducing transaction costs can have negative implications when it leads to a knowledge disparity of some market participants with respect to others. Similarly, Turpin (2014, p.350) argued that lower transaction costs in BITCOINs may attract more investors who previously could not **trade** due to high transaction costs, but, at the same time, placed these new investors at a high comparative disadvantage vis-à-vis their more experienced peers, thereby rendering them more vulnerable to "the risks and dangers of trusting their wealth to a virtual currency".

Fixed supply: The algorithm underpinning BITCOINs allows for the **minting** of a fixed amount of BITCOINs (*cf.* Nakamoto, 2008). Just as **gold** reserves are limited, the supply of BITCOINs cannot be inflated by governments. This characteristic has been viewed as an opportunity for growth for many persons whose **investments** were otherwise damaged by central bank mismanagements, by international conflicts or by oppressive governments – *i.e.* Argentina, Iran and China (*Cf*. Turpin, 2014). Central banks, on the other hand, may see this as a threat to their monetary policy. Moreover, while hyperinflation can be detrimental to growth, inflation is meant to stimulate trade. Conversely, contesters of BITCOINs argued that the deflation

introduced by the BITCOIN algorithm was likely to lead to hoarding behaviour, mimicking a global scale Ponzi-scheme, and lead in the end to a long term depreciation of **prices** quoted in BITCOINs (Turpin, 2014).

Highly volatile*:* BITCOIN prices have varied from nothing to close to 1000US **Dollar** per BITCOIN (see www.bitcoincharts.com) from 2009 to 2014. While Plassaras (2013) argued for the International Monetary Fund (IMF) to back BITCOINs, in fact no government or supranational **organization** sets BITCOIN's value. Instead, this value is the real-time intersection of **supply** and **demand** of BITCOINs in the **marketplace** (Bryans, 2014). **Volatility** is therefore a natural consequence, and Grinberg (2011, p.175) argued that this will ever more happen if *"unexpected changes in the inflation rate imposed by the software developers or others, a government crackdown, the creation of superior competing alternative currencies, a deflationary spiral"* or technical problems **compromising** anonymity or **allowing** for the theft of BITCOINs would take place. Nevertheless, Grinberg (2011, pp.174-175) maintained that being backed by governments is not a must for a currency to survive as a **payments** system. As long as trust persists, the currency will not fade away, just as the value of Iraqi Swiss Dinar did not fluctuate over a period of 10 years, while not being backed by any **commodity** or government (Grinberg, 2011).

Some BITCOIN proponents argued that volatility did not depend on the lack of government backup but on the inherent novelty of the coin. With higher widespread adoption among consumers and merchants, the mechanisms to counteract speculator driven fluctuations would eventually develop and volatility would therefore decrease (Turpin, 2014). Others argue that volatility was driven by speculators, wishing to make a gain on the **exchange rate** between BITCOINs and **fiat** currencies. In fact, until energy costs are paid in BITCOINs, the BITCOIN ecosystem is not self-sustainable (Brito & Castillo, 2013). As a result, BITCOINs were not a lucrative storage of value. Instead, when used as medium of exchange, merchants could ride over fluctuations in exchange rates, by pricing their goods in traditional currency and accepting the equivalent in BITCOINs and transferring them immediately. The merchants would therefore not hold BITCOINs for long, thereby allowing for them to change value (Brito & Castillo, 2013).

2.3. Technical opportunities and threats

Novel digital solution: The BITCOINs open source software uses cryptographic primitives to offer a novel solution to value transfers in the absence of trustworthy third-parties. The BITCOIN **protocol** can be adapted and developed upon, such that other types of data can be transported: *i.e.* sensitive information (BitMessenger), contracts (Smart Property of Mike Hearn); but also to improve anonymity and security (BitLaundtry). Luther and Olson (2013) argued that the novelty of the BITCOIN protocol is its public ledger – *i.e.* an actual form of

economic memory. If humans have imperfect memory, money is needed to 'remind' which promises are truthful. As such, Luther and Olson (2013) pointed to a soar in the demand for BITCOINs when the costs of storing and verifying traditional money soared, pertaining to the Cypriot crisis. As such, proponents of BITCOINs argue that the small scale contract possibilities, the potential for economic memory creation and the innovation potential of BITCOINs were worth taking the regulatory risk. To the contrary, adversaries of BITCOINs, among which Hugues, suggested that the protocol offered criminals too many escape parameters, and that innovation claims should largely be ignored if based on deregulation (Trautman, 2014, p. 37). BITCOINs require users to hold a certain degree of IT knowledge, such that they avoid deletion of their wallet or theft. In 2014 there have been many successful hackings of joint wallets and trading platforms (*cf*. Brito & Castillo, 2014).

Secure solution: Proponents of BITCOINs argued that BITCOINs are more secure that regular money as they cannot be confiscated by governments, law enforcement or any other third parties. Criminal users of **Silk** Road have made this point clear as, although Silk Road was shut down by the FBI and its creator was indicted, few customers and collaborators were identified, prosecuted or trialled, and moreover, few BITCOINs were forfeited by law enforcement (Lane, 2014, pp. 526-530). Nevertheless, BITCOIN's security is not infallible. Especially with the increasing value of BITCOINs, IT savvy criminals could target BITCOIN services as well as individual BITCOIN wallets (FBI, 2012, p.8). **Malware** constructed by malicious actors could be deployed on private computers to steal private **keys** but also to use the computers either to mine BITCOINs or to create botnets and to coordinate Distributed Denials Of Service (DDOS) **attacks** against third party BITCOIN exchange services or wallets (FBI, 2012, pp.8-9). Furthermore, the BITCOIN ecosystem offers a best disguise to financial transactions once its ecosystem is large. With small or decreasing ecosystems, transactions are relatively easier to track back via meta-analysis (Villasenor *et al.*, 2011).

Power to the miners: Miners stand at the core of the BITCOIN ecosystem. Miners are in fact computers equipped with a certain open source software that are trying to solve the **cryptographically** imposed problems that allows them to validate **packets** of transactions and in turn rewards them for their effort with newly generated BITCOINs (*cf.* Nakamoto, 2008). As a result, mining is a costly affair and since the **genesis** of the first BITCOIN it becomes ever more costly. Computers consume energy to perform the calculations required and contesters of BITCOINs argued that this drove the transaction costs high (*cf.* O'Dwyer & Malone, 2014). Moreover, as the supply of BITCOINs decreases miners might have to rely on 'bounties' from transacting parties – a fact that would once more increase transaction costs – or on changing the shape of the supply curve to avoid decreasing rewards to mining (Kroll *et al.*, 2013). Conversely, BITCOIN proponents argued that better **hardware** (higher **CPU** processing power), better software (fewer **bugs**) and the better positioning of mining **pools** in countries or areas

with lower energy prices could additionally reward miners for their expenses, while keep transaction costs low (Brito & Castillo, 2014).

Competition among miners is beneficial because it ensures that transactions are validated at the lowest cost and as fast as possible. In fact, this potentially perfect competition makes that BITCOINs have a cost comparative advantage over oligopolistic payments that are dominated by PayPal, MoneyGram, Western Union and SWIFT. Perfect competition is wished for as any mining pool larger than 50%+1 of the total computational power gives receives a veto vote in the BITCOIN technological democracy and therefore the power to preclude transactions from taking place (Kroll *et al.*, 2013). Moreover, as Turpin (2014, p.340) discussed, instead of using this veto to double spend BITCOINs, it may be more profitable to use the computational power to mine BITCOINs. But since this is a fundamental flaw of the BITCOIN ecosystem, one must take into account the fact that in a shrinking population of BITCOIN users, obtaining a veto position is easier, and that once the maximum supply of BITCOINs is reached, the benefits from having veto power will materialize even more. In this context, security proponents may be threatened by the Financial Crimes Enforcement Network (**FinCEN)** (2013) administrative guidance that places some miners under the incidence of the amended US Banking Secrecy Act of 1970[82], when they *"mine a convertible virtual currency [not] solely for [their] own purpose",* and that consequently reduces the number of miners.

2.4. Studies on BITCOIN markets and users

BITCOIN users: Triggered by the research of Kristouflek (2013), Yelowitz and Wilson (2015) used Google trends to study the "clientele driving interest in BITCOINs" in the US. They constructed proxies for four possible clienteles: geeks, speculators, libertarians and criminals, by modifying the Google trends search to "BITCOIN + code for specific clientele". Their codes are "computer science", "silk road", "free market" and "make money", respectively. Although creative, there is little theoretical underpinning for their research, in our view. Moreover, their results are not consistent with other findings of the literature (*i.e.* Lui, 2013), as they showed that 'computer programming' and 'crime' are related to BITCOIN interests whereas 'libertarian' and 'investment' are not. Conversely, Lui (2013) used an online survey platform[83] to interview BITCOIN users on their intentions. The conclusions on the basis of more than 1000 interviews were that a third of BITCOIN users are male and libertarian, that curiosity, profit and politics are the main investment drivers and that the overall usage of BITCOINs is for non-criminal purposes. As Böckenholt, Barlas and van der Heijden (2009) showed, respondents have no incentive to report truthfully, to questionnaires even when their anonymity is practically anonymous. Therefore, this type of research has, in our view, severe biases, especially when investigating the potential criminal use of BITCOINs.

[82] Banking Secrecy Act of 1970, Pub. L. No. 91-508.
[83] Lui (2013), downloadable at http://simulacrum.cc/2013/03/04/the-demographics-of-bitcoin-part-1-updated/

The market for BITCOINs: Buchholz *et al.* (2012) are among the first to analyze the evolution of BITCOIN prices using among others Google trends as proxy for investors' attention. Noting a lack of economic works on BITCOINs vis-à-vis a relative good legal and technical analysis of BITCOINs, they modelled the demand for BITCOINs as a demand for fiat private currency issued by a pool of mostly non-tech-savvy users. Their research question is: how does online manifested attention to BITCOINs translate into the demand for BITCOINs. They found that Google trends Granger cause the BITCOIN transactions volumes in the short run. Similarly, Kristoufek (2013) studied the relationship between Google trends and Wikipedia trends respectively, and the price of BITCOINs. He showed that the relationship was significant, yet he did not comment on the fact that proxying investor attention with Wikipedia trends and with Google trends gave significantly different results. Which of the two proxies should be used and what do they really capture, remain unanswered.

Ciaian, Rajcaniova and d'Artis Kancs (2014) criticized the previous two studies for separately studying the impact of BITCOIN's price. Conversely, they brought together supply and demand fundamentals, investor attention (*i.e.* Google trends) and global financial indicators. They found that market fundamentals could explain prices, whereas investor attention proxies had ambiguous effects and global financial indicators had no effect. Their regressions employed many explanatory variables and relied on a relatively small sample. Interesting developments were made by Bouiyour, Selmi and Tiwari (2014). They analyzed Granger causality for two relationships: BITCOIN price and transactions, and BITCOIN price and Google trends. They analysis is especially interesting as they took into account the difference in frequencies that these variables had, and, in fact, analyzed these relationships both across highly volatile, across medium and across very stable periods. Additionally, Glaser *et al.* (2014) analyzed the impact of price, Wikipedia searches and price on volumes of BITCOINs traded, as well as on the volume of BITCOINs exchanged outside trade platforms. This separation of volumes allowed for testing what influences the BITCOIN currency, and what influences the BITCOIN commodity. Following Glaser *et al.* (2014), we tested our investor attention proxies on the volume of BITCOINs traded outside known stock-exchanges.

All these financial studies considered the market for BITCOINs to be small sized, such that it could, in fact, be altered even by small sized investors, with little financial investment training. Considering the ambiguity associated with the paradigm shift, the rise and fall of new BITCOIN gurus (*i.e.* MtGox), the large volatility in the BITCOIN prices came as no surprise. In the novelty, in the lack of (coordinated) regulation, many saw opportunities, others saw threats, and these were all discussed online and so the Google and Wikipedia trends proxies for investor attention performed well.

With one exception, Google and Wikipedia trends were so far the only explanatory variables for BITCOIN trade volume and price volatility, and both were used as proxies for investor

attention. Although initially attractive, these proxies have significant drawbacks. First of all, the methodology behind the construction of these proxies is not transparent, thereby not ensuring that the proxies can be replicated. For example, Kristoufek (2013) reported different results when measuring investor attention with Wikipedia trends than when measuring it with Google trends. Is this a defect of the proxy construction or do the two, measure the interest of different groups? Finally, and importantly, it is interesting to know what financial investors look for when Googling "BITCOIN", but what they actually receive as information is what triggers their decision to invest.

3. The model

We took the view that BITCOIN is a form of currency with two particular features: a fixed supply and no underlying value but trust. Because the supply of BITCOINs is fixed, the price of BITCOINs is determined solely by fluctuations in demand (*Cf*. Buchholz *et al.*, 2012). Furthermore, we assumed that all our actions that leave a digital trace may influence other people's actions (*Cf*. Bordino, Battiston, Caldarelli, Cristelli, Ukkonen & Weber, 2012). In other words, we assumed that opportunities and threats expressed online (Section 2) and returned to Google queries on "BITCOIN" support BITCOIN investment decisions.

Important news or information is not reflected in the market until investors pay attention to it (*Cf*. Huberman & Regev, 2001; Hirschleifer, Hou, Teoh & Zhang, 2014). In order for investors to pay attention to it, information must first be available to them. When querying "BITCOIN" in Google, investors already showed interest in BITCOINs and the then returned information helped shape their decision. The volumes of new financial, technological and respectively legal texts returned upon these queries, reflects thus, the amount of new threats and opportunities investors may pay attention to. All things considered, our measures therefore reflect investor attention to the legal, financial and technological uncertainties of BITCOIN. This seems an innocuous assumption given that the literature on BITCOINs so far has raised more questions than has given answers (*Cf*. Brito & Castillo, 2013). Subsequently, should this information be multifaceted and abundant, can we expect investors to be selective about which to process (*Cf*. Peng and Xiong, 2006)? Importantly, we tested investors' ability to perfectly incorporate this information into their trading activity. If this is not the case, if investors have limited attention to BITCOIN relevant information (*Cf*. Peng *et al.*, 2007), we investigated which type of information they allocated resources to.

In order to do so, we distinguished three types of groups interested in BITCOINs: speculators who see it as a gambling tool, users (*i.e.* legitimate or illegitimate businessmen that accept and use BITCOINs and libertarians) and miners (*i.e.* geeks) (*Cf*. Yelowitz & Wilson, 2015). These

groups interacted on two markets, which we called the financial markets and the non-financial markets (*Cf*. Glaser *et al.*, 2014). In Figure 4.1, 'A' marks the users and speculators group and 'B' marks the miners group. Each group acquired BITCOINs differently and potentially for different purposes. The miners needed to invest technology to mine BITCOINs, and once in possession, they could exchange them for goods on the non-financial markets or for other currency on the financial markets. Users and speculators could acquire BITCOINs by offering goods and services to BITCOIN owners or by buying them at the current market price from the BITCOIN exchange. While traders used BITCOINs as currency to trade for goods and services, following the intuition of Glaser *et al.* (2014), speculators in BITCOINs did not engage in financial transactions. Instead, they acquired BITCOINs and stored them with the intent of selling them later in order to make extra-ordinary returns.

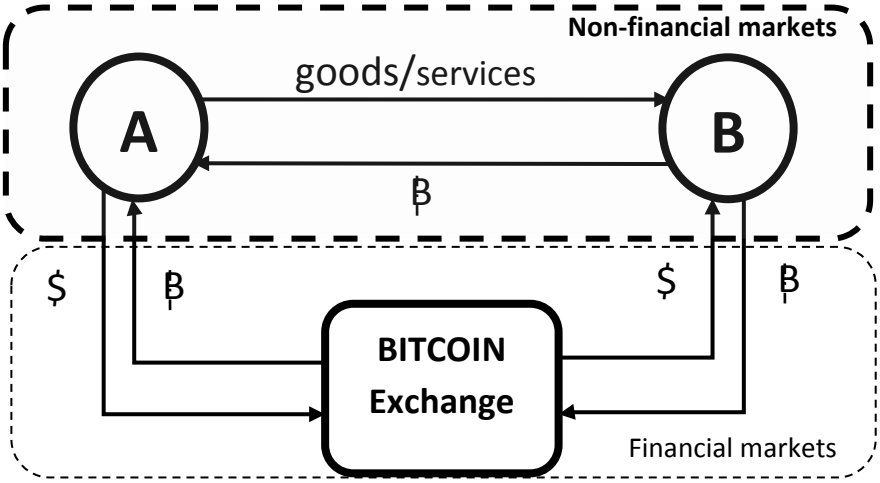

Figure 4.1: A graphical outline of the transaction dynamics with BITCOINs within the financial markets and outside them.

Using this framework, we proposed three hypotheses, following three streams of literature developed on the interplay between investor attention and market performance. Standard asset pricing models (Ross, 1976; Merton, 1973) assumed that investors are able to comprehend new information instantly and that prices of assets incorporate any new information instantly. Conversely, psychology founded economic studies found that humans have limited attention and therefore need time to process information (Kahneman, 1973; Peng *et al.*, 2007). Consequently, if investors have limited time resources, and if faced with high volumes of information, they must allocate their attention to information that is genuinely needed or urgent to process (*Cf*. Peng and Xiong, 2006).

Karpoff (1987, pp.112-116) gave an overview of the empirical evidence supporting the statement that transaction volumes and absolute price changes are positively correlated. Karpoff (1987, p.121) concluded that *"simultaneous large volumes and large price changes*

can be traced back to their common ties to information flows or their common ties to a directing process that can be interpreted as the flow of information". Importantly, since our measures of information may reflect both threats and opportunities for BITCOIN investors, we expect them to influence the volume of transactions more than prices. If information reflects both opportunities and threats, then prices cannot be used to measure investment attention, but transaction volumes should increase when investors incorporate this information, and should indicate the adjustment of BITCOIN trading activity (*Cf*. Glaser *et al.*, 2014).

Hypothesis 1: In response to a shock that increases uncertainty about BITCOINs, speculators, miners and users are able to process novel information perfectly. This leads to an instant increase in the BITCOIN trading volatility with no subsequent impacts.

We assumed a standard asset pricing model setting, where shocks and novel information is immediately dispersed in the market place and where investors incorporate it in trading and in prices instantly. There are therefore no lags to the trading volatility driven by this novel information. In contrast, Hypothesis 2 proposed that investors cannot resolve uncertainty immediately. And, as proposed in chapter 2 of this thesis, entropy could be used for measuring the information value of a signal (Shannon, 1948). Novel signals first need to be understood, and only once they are understood they reach their maximum potential of reducing uncertainty (Fig. 2.1). In this framework, shocks increasing uncertainty had to be understood. This led to lags in the information driven trading volatility. As time progressed, these lags should have decreased in magnitude.

Hypothesis 2: In response to a shock that increases uncertainty about BITCOINs, given their limited temporal capacity to resolve uncertainty, speculators, miners and users take time to fully process novel information and to resolve uncertainty. This leads to an increase in the BITCOIN trading volatility in the short run that gradually decreases over subsequent periods.

We then assumed that BITCOIN interested groups additionally had limited resources to allocate to reading and understanding the information published online on BITCOINs. Not only did understanding the information take time, but time was limited. This model adheres to a new strand of behavioural financial studies (*Cf*. Peng *et al.*, 2007; Sims, 2003). We therefore, hypothesized that the earlier identified BITCOIN groups prioritized certain types of information, as the latter were more relevant to their case.

Hypothesis 3: Given the limited resources to dedicate to resolving uncertainty that speculators, miners and users have, they only respond to shocks that increases uncertainty about BITCOINs and that are relevant to their position. Traders on financial markets are likely to prioritize financial and technical information, whereas traders outside financial markets are likely to prioritize legal information.

When trading on BITCOINs, we assumed speculators exhibited forward looking behaviour in order to maximize their investments. Attention to price fluctuations, to market uncertainty could have increased their payoffs. Similarly, attention to technical information may have improved mining, may have improved the security of wallets and therefore may have prevented financial losses. On the other hand, since BITCOINs could not have credibly been forbidden, legal information would have been translated into financial information and would not have interested BITCOIN speculators.

Conversely, since using BITCOINs to buy services and goods did not suffer from the price volatility of BITCOINs (*Cf.* Brito & Castillo, 2013) financial information may not have been prioritized by traders outside financial markets. Also, under the shield of anonymity, transacting in BITCOINs had reduced the transaction costs, both for legal and for illegal businesses. Legal information would have therefore been interesting for parties transacting in BITCOINs outside financial markets. Equation 4.1 formalizes these assumptions.

$$preference = \begin{cases} I_F \succcurlyeq I_T \succcurlyeq I_L, \ if\ trading\ in\ BITCOINs\ on\ financial\ markets \\ I_L \succcurlyeq I_T \succcurlyeq I_F, \ if\ transacting\ in\ BITCOINs\ outside\ financial\ markets \end{cases} \quad (4.1)$$

This methodological framework and these assumptions allowed us to, for the first time, model and further test the interest in particular types of information exhibited by three groups of investors: speculators, miners and users, and their impact on this information on the demand and price of BITCOINs.

4. Methods and data

We collected market data on the weighted daily price of BITCOINs (in US Dollars), on the daily traded volumes in US Dollars and on the daily traded volumes in BITCOINs. We also collected data on Wikipedia daily, and Google weekly, BITCOIN queries. Just as Glaser *et al.* (2014), we constructed a measure of the BITCOIN network value – *i.e.* transactions employing BITCOINs that involved goods and services and took place outside stock exchanges. The latter measure resulted from subtracting the volume of total transactions on financial markets (in BTC) from the total volume of transactions recorded in the block-chain. Table A4.1 describes the data and the sources used.

We additionally used a novel measure of investor attention, where attention was split into attention to the legal, the technological or the financial aspects of BITCOINs. This is a self-constructed measure that departed from Google's indexed BITCOIN relevant information (*i.e.* the information freely available to internet users from 01-01-2010 to 01-01-2014). Section 4.1 reports on the construction of a random sample of information available to investors. Section

4.2 reports on the operationalization of this sample into a proxy for investor attention toward legal, financial and technological properties of BITCOINs.

Generating the BITCOIN information corpus

We estimated what potential investors had as available information on BITCOIN in the period 01-01-2010 to 01-01-2014. For this purpose, we constructed a corpus of information that Google returned to potential BITCOIN investors who searched for 'BITCOIN' on Google in this period. We then filtered this corpus such that it reflected, as much as possible, only information relevant for BITCOIN investors (Fig. 4.2). In constructing and analyzing the corpus we kept close to the qualitative data analysis methods of Glaser and Straus (1967) and to the data coding techniques of Miles and Huberman (1994).

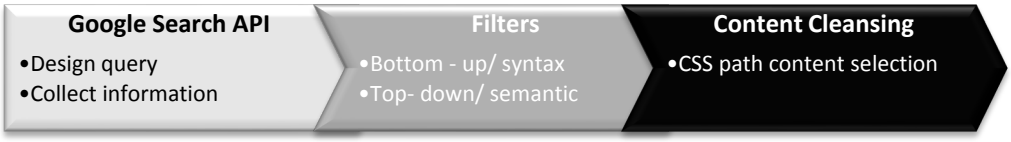

Figure 4.2: Genesis of the BITCOIN on-line information corpus.

Data Gathering: We collected information on BITCOINs available to investors wanting to understand what BITCOINs were, how they worked, who traded in them, at what price, why, what regulations they were subject to etc. For this purpose, we used Google Search API to construct and retrieve Google search results for each day of period 1-January-2010 to 1-January-2014. The query was customized to bring for each day in this interval all documents indexed by Google robots that (1) contain the word 'Bitcoin' in their contents, title or meta-data (*i.e.* publisher, author, author affiliation) and (2) that were Google indexed as relevant for that specific day. In our endeavour we met most of the challenges described by Christin when he researched the Silk Road market (*Cf*. Christin, 2012, pp. 4-7). We used Google Search API (Application Programming Interface), as previous related research revealed it as an informal yet content-rich source of information. Google is used by many researchers as more a scientific investigation tool than a search engine (*Cf*. Preis, Moat, Stanley &Bishop, 2012), as it provides both an approximation of the state of the world at any given time. The Google query returns a total of 244,299 BITCOIN relevant documents published in this interval, belonging to 59,459 domains. We considered the first date when a document was indexed by Google as its authoring/ publishing date.

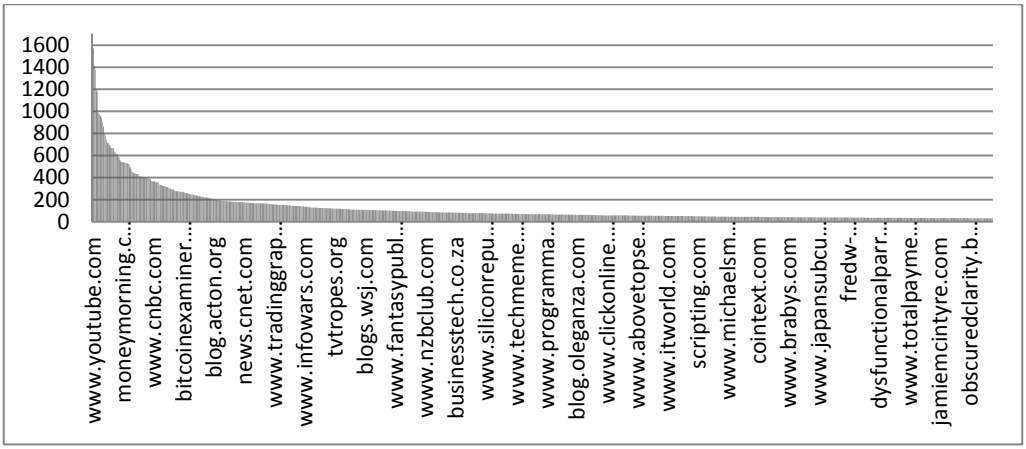

Figure 4.3: Top 1000 most prolific domains, in terms of BITCOIN articles. The domains are reported in order of the number of articles published on BITCOINs that they contained between 2010 and 2014.

Figure 4.3 reports on the distribution of documents per domain. Distribution of number of documents per domain revealed that a relatively large fraction of the BITCOIN documents belonged to a relatively small fraction of domains: the top 300 domains with more than 100 documents published per domain accounted for 88446, *i.e.* more than 36% of the total number of documents; the top 1,000 most prolific domains, each with 30 documents or more published per domain, accounted for 125,210 documents, *i.e.* more than 51% of the BITCOIN corpus, and the top 1,550 most prolific documents with more than 20 documents published per domain accounted for 138,717 documents, *i.e.* 56% of corpus.

Data Filtering: We used manifest content analysis method, *i.e.* we only analyzed available information that could be downloaded at the time of analysis, from the total list of BITCOIN relevant documents that the Google Search API returned. From the total 244,299 documents, 144,000 were available and could be retrieved without special credentials. The rest we eliminated from our study sample. The 144,000 downloaded documents were saved for further filtering and cleansing. We then applied two filters to clean the corpus (a “Bottom-up” filter and a “Top-down” filter) and superimposed them to obtain a stable set – a corpus with the highest possible quality of information. While collecting the BITCOIN corpus, we discussed among us and with our colleagues, what this literature found and what the raw data was showing us. This iterative process enabled us to design these filters, and is in line with the grounded theory approach instructions of Glaser and Strauss (1967) and Corbin and Strauss (1990).

By means of a “Bottom-Up” filter we cleaned the original corpus at the syntax level. The filter imposed that relevant documents contained the word “BITCOIN” (case insensitive) in their

title or content file.[84] The filter also imposed that documents were text only,[85] written in English and belonged to one of the supported formats: PDF, HTM, TXT, ASCII, DOC. All documents not meeting these criteria were dropped. The "Bottom-Up" filtered corpus thus contained 78,692 relevant documents, belonging to 21,082 domains. By means of a "Top-down" filter we cleansed the "Bottom-Up" filtered corpus at the semantic level. The filter first imposed that only domains indexed in the Google Search API at least 20 times in the period 01-01-2010 to 01-01-2014 should be considered.[86] Two human experts then manually indexed the remaining domains and eliminated 1056 domains that contained non-relevant at a semantic level – *i.e.* where the word "BITCOIN" occurred in side-bar advertisements only – or at a syntax level, as described above. The stable corpus that resulted after applying both filters contained 13,287 documents, belonging to 2,304 distinct domains (Fig. 4.4).

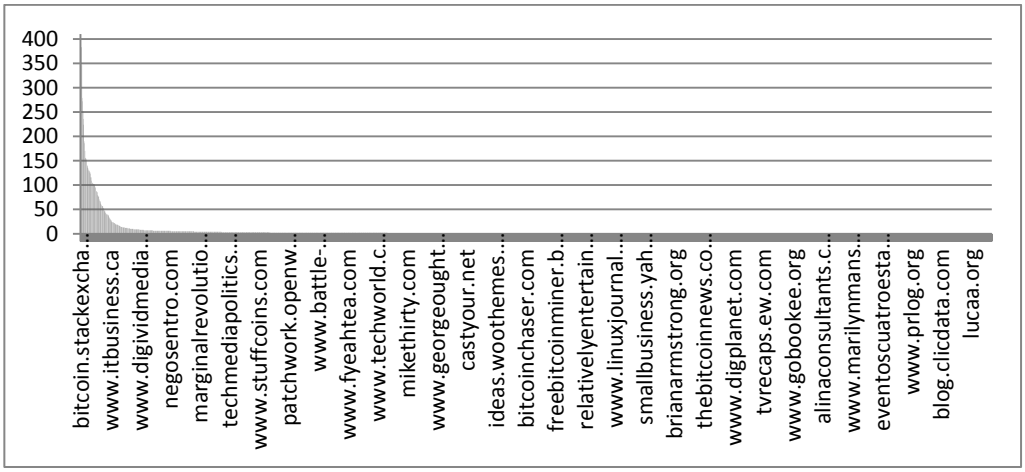

Figure 4.4: Distribution of documents per domain in the filtered relevant corpus. Top 100 most prolific domains from 2,297 domains account for 13,287 analyzed documents.

Content Cleansing: As Miles and Huberman (1994) suggested, we applied the 'data reduction' process. For HTML content we used CSS paths to identify content specific information in the document contents and to filter out non-relevant elements. This allows us to reduce noise by removing from the content of a document all parts that were not relevant to the actual analysis, *e.g.* by removing words that contained site-specific contents irrelevant to the document, menus, copyright, privacy disclaimers etc. We constructed a domain-specific document scraper, which took into account the logical structure of documents from that

[84] The scraper searched for the occurrence of the case insensitive word 'BITCOIN' in the document content, and scrapes then cleansed the contents.

[85] Scrapers filtered out empty documents; documents belonging to domains ending in .pl, .pt, .ru, etc.; documents containing non-ASCII characters.

[86] These were the domains most frequently publishing BITCOIN related information and therefore more likely relevant to the BITCOIN community.

domain. This allowed, for instance, that all the articles of a particular website were processed uniformly. When the CSS path extractor did not produce any output, the entire text content was used. This ensured that no content was lost.

5. Operationalizing investor attention

As Section 2 of this chapter showed, describing BITCOINs is a fairly simple and brief exercise. Exploring the possibilities that BITCOINs offers, until coming to the conclusion that they are either realistic, short-termed or simply threats disguised as possibilities, has been a much more challenging exercise.

Functional taxonomy: Following Miles and Huberman (1994), we organized the corpus described in section 4.1 according to the source of the material. This gave us a good 'data display' (Miles & Huberman, 1994) if only on a structural level – *i.e.* we knew which sources originated most information on BITCOINs over time. We then applied a functional taxonomy (Appendix A4.2). This taxonomy was built iteratively in a top-down fashion starting from the existing taxonomies applied to online news by among others Google, Yahoo and Reuters, and adapting them to cover a broader range of sources. The corpus was classified manually by three independent human experts, the resulting taxonomy being the intersection of their individual classifications. We thereby ensured the development of 8 functional categories, the relationships among them being *"developed and verified as much as possible during the research process"* (Corbin & Strauss, 1990, p.422).

Semantic taxonomy: On the basis of the BITCOIN corpus and independent from the functional taxonomy, we clustered the corpus at a semantic level. The size of the corpus required the usage of an automated process. We applied a combination of deductive and inductive methods in the semantic analysis of the corpus. Before coding the data, we thought about the main themes that the BITCOIN discussion generated. Section 2 reviewed the literature in a way that exposed the main sectors where the BITCOIN community saw opportunities and threats – the technical, the financial and the legal sector. Unable to read and code manually the 13.800 documents corpus, we started from advancing codes on these themes from the MPQA Subjectivity Lexicon[87] (*Cf.* Wilson, Wiebe & Hoffmann, 2005). Three human experts selected category codes, *i.e.* tags that could be assigned to any of the three themes: TECHNICAL, FINANCIAL, and LEGAL. Their intersection formed the human-generated set of tags. For each theme, we used the codes to identify all the documents containing at least one code in their text and then selected the top 500 most frequent used words in this group of documents. The experts reviewed this frequent list of words and checked whether they are indeed related to the theme, and only this theme. If they did, they became

[87] MPQA Subjective Lexicon, downloadable at http://mpqa.cs.pitt.edu/lexicons/subj_lexicon/

computer-generated codes and were added to the human-generated list of codes. The process of triangulation was iterated, until reaching a stable set of codes that was valid, all-encompassing and mutually exclusive along the themes (*Cf*. Miles & Huberman, 1994). Table 4.1 reports on the set of codes, per theme that were stemmed and used in classifying the corpus at a semantic level.

Table 4.1: Themes and codes used to classify the BITCOIN corpus.

Themes	Representative codes [a]
TECHNICAL	**Attack; cpu**; bitcoin-qt; **block**; breach; **key**; **bug**; **chain; compromise**; **cryptography**; energy; nodes; **genesis**; glitch; gpu; **geek**; **hardware**; homomorphic; informatics; machine; **miner; peer; protocol**; **processor**; **packet**; technology
FINANCIAL	**Bank**; bond; Btc; **buy**; **capital**; **chart**; commodity; **currency**; **credit**; **demand**; **deflation; donate**; **dollar**; euro; **exchange**; **fiat**; **financial**; forex; flow; **gold**; **inflation**; **investor**; **market**; **mint**; **pay**; **Ponzi**; **price**; **poverty**; purchase; sell; **supply; trade**; **transaction**; treasury; **volatile**; withdraw; r**emittance**; **yen; Yuan**
LEGAL	**Agency**; arrest; anarchist; **Austrac**; authority; **botnet**; control; **crime**; **Cyprus**; deter; **enforce**; **federal**; **fight**; **Fincen**; **forfeit;** Hezbollah; fraud; **legal**; **investigate**; jail; **jurisdiction**; **law**; **Liberty**; **launder**; narcotic; **malware;** police; **politics**; **prosecute**; **regulate**; sanction; **Silk**; society; terror; state; **tax**; Trac*f*in; transnational; underground; **trace**; war

Note. [a] presented as non-stemmed codes in the table. The identification of codes in text was automated on the basis of the stems provided by the tm package in R.

Generating the investor arousal proxies

For each document i in the corpus we were able to calculate the total frequency of stemmed technical, legal and financial codes. Let TF_i^T,TF_i^F and TF_i^L denote the total frequency of technological, financial and, respectively, legal codes found in document i. For each document i we also know the functional category it belongs to. Let $C_i \in \{T, L, F, N, B, M, A, D\}$[88] denote the category document i takes, the options being the capital letters of each category presented in Table A4.2. We recognized that several themes can be treated by one document. Nevertheless, in order to ensure that the final investor attention proxies were distinct, we added on top of this filter a functional filter, such that each document was classified as belonging to one of the 3 categories (Equation 4.2).

$$information_i = \begin{cases} technical,\ if\ C_i \in \{T, M, B, N, A, D\}\ and\ TF_i^T \geq TF_i^F\ and\ TF_i^T \geq TF_i^L \\ legal,\ if\ C_i \in \{L, M, B, N, A, D\}\ and\ TF_i^L \geq TF_i^F\ and\ TF_i^L \geq TF_i^T \\ financial,\ if\ C_i \in \{F, M, B, N, A, D\}\ and\ TF_i^F \geq TF_i^T\ and\ TF_i^F \geq TF_i^L \end{cases} \quad (4.2)$$

Table 4.2 reports on the correlation between these three measures and the correlation with traditional measures of investor attention: Google and Wikipedia trends. Google trends were

[88] The acronyms correspond to a functional taxonomy. All functional taxonomies we used are described in Table A4.2.

least correlated with our measures, whereas Wikipedia trends were significantly correlated with all three. Figure 4.5 further depicts the number of technical, legal and financial documents returned by Google to the query "BITCOIN", over the period of interest. More documents introduced financial information than legal of technological information and legal information displayed most volatility clusters.

Table 4.2: Correlation between Wikipedia trends, Google trends and three investor arousal proxies.

Pair-wise correlations	Google trends	Wiki trends	IA_FIN	IA_LEG
IA_FIN	0.34***	0.5***		0.63***
IA_LEG		0.4***	0.63***	
IA_TECH	-0.16**	0.25***	0.5***	0.47***

Note. *p< .1, **p< .05, ***p< .01.

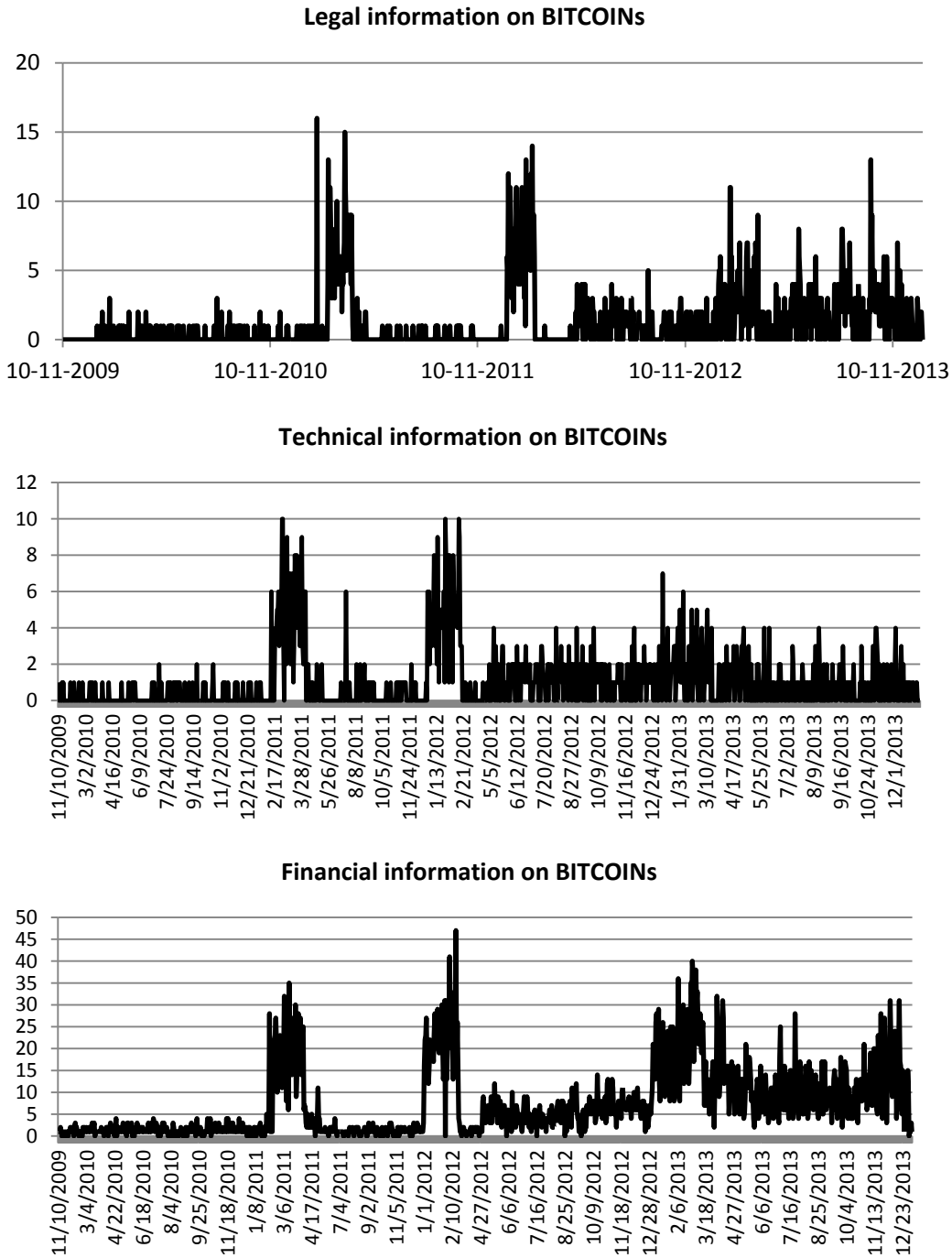

Figure 4.5: A visual description of Investor arousal proxies: legal, technical and financial information plotted over time.

6. Results

Time series often need to be transformed in order to successfully apply sophisticated methods on them. Such transformations are due to the assumption imposed by most methods, such as the constant variability of time series over time. Transforming time series therefore allows for a better understanding of the driving forces once cycles and low frequency content is removed (Kendall & Ord, 1990). Just as Kristoufek (2013) and Buchholz *et al.* (2012) we stabilized variance across time by using log-transformations, and took out trends by using first differences. Additionally, we solved missing data problems by using weekly averages instead of daily data.[89] Figure A4.1 reports on the histograms of our time series, whereas Figure A4.2 shows the double logarithmic correlations between our proxies and the price and the volumes of transactions on and outside financial markets.

We checked for stationarity and unit root using the KPSS (Kwiatkowski, Phillips, Schmidt, Shin) and the Augmented Dicky-Fuller tests.[90] The 'null hypothesis' in the KPSS test is that the time serie is stationary, whereas the 'null hypothesis of the Phillips-Perron and of the ADF test is the presence of a unit root. Consequently, when the KPSS null hypothesis is rejected, while the ADF null hypothesis is not rejected at 95% significance level at least, the variable of interest is non-stationary. We used the KPSS test in conjunction with the ADF/ DF-GLS tests to investigate whether our series are fractionally integrated – *i.e.* neither I(1) nor I(0) – and found no such evidence. Table 4.3 reports on the stationarity of the measures, given the optimal choice of lags. As the table shows, all our variables aside the investor legal attention are I(1) time series, since they become stationary once first differences are taken.

Table 4.3: Checks for stationarity and unit-root in the time series using the KPSS and the ADF tests.

Variable	KPSS	ADF	DF_GLS lags	Stationary
Investor financial attention				
• **Weekly-log level**	0.124;p<0.1	-3.03;p>0.1	11	N
• **Weekly-first dif log**	0.018;p>0.1	-6.9;p<0.01	10	Y
Investor legal attention				
• **Weekly-log level**	0.041;p>0.1	-5.4;p<0.01	1	Y
Investor technical attention				
• **Weekly-log level**	0.127;p<0.1	-3.36;p>0.05	13	N
• **Weekly-first dif log**	0.025;p<0.1	-5.08;p<0.01	12	Y
Stock Market Traded Volumes (BTC)				
• **Weekly-log level**	0.276;p<0.01	-1.44;p>0.1	11	N
• **Weekly-first dif log**	0.024;p>0.1	-18.4;p<0.01	0	Y
Non-market Transacted Volumes (BTC)				
• **Weekly-log level**	0.359;p<0.01	-1.78;p>0.1	4	N
• **Weekly-first dif log**	0.019;p>0.1	-6.85;p<0.01	4	Y
Price BITCOINs (USD)				

[89] As robustness check, we ran the same analyses on the daily data and found that the results were consistent.
[90] In selecting the optimal number of lags for the ADF unit root tests we used the *dfgls* unit root test.

• **Weekly-log level**	0.149; p<0.05	-2.2; p>0.1	10	N
• **Weekly-first dif log**	0.09;p>0.1	-3.87;p<0.01	9	Y
Price Volatility				
• **Weekly-log level**	0.248;p<0.01	-2.17;p>0.1	8	N
• **Weekly-first dif log**	0.097;p>0.1	-4.79;p<0.01	8	Y

We then tested the co-integration between our time series. We used the Engle-Granger and the Johansen tests as they indicate whether the non-stationary processes share a trend or not (Engle& Granger, 1987; Johansen, 1988). We considered the Engle Granger test to be more robust alternative to the Johansen's test given the fewer distributional assumptions, so every time the two test yield contradicting results, we followed the Engle Granger results. We found that the transaction volumes on financial market, the investor financial attention and the investor technical attention respectively, are the only two pairs of co-integrated time-series. We then made use of Vector Error Correction Models (VECM) for these two pairs and of Vector Auto Regression (VAR) for the rest. Figure 4.6 shows that some of our variables of interest exhibit clustering in the volatile periods. We thus employed Heteroskedasticity Autocorrelation Correction standard errors in our bi-variate analyses. This is in line with the work of Kristoufek (2013). We used the Akaike and the Schwartz-Bayesian information criteria to select the optimal lag-order to employ in our VAR and VECM specifications, respectively (*Cf*. Ivanov & Kilian, 2001).

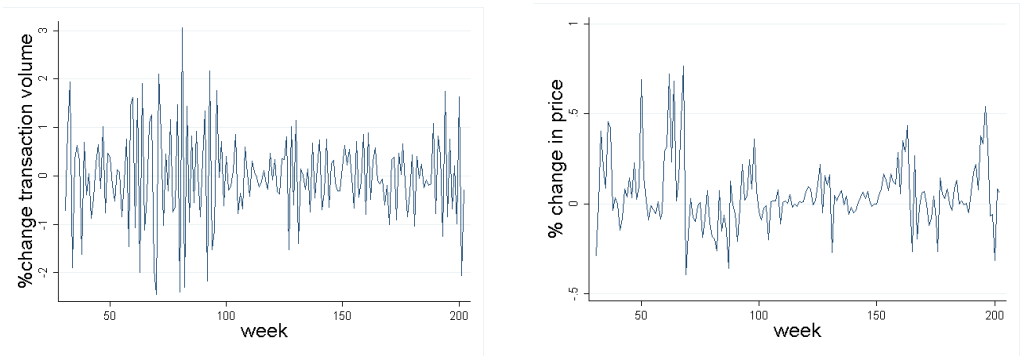

Figure 4.6: Evolution of BITCOIN price and transaction volumes over time. The left-hand-side chart plots the percentage changes in the volume of BITCOINs traded on financial markets across time, whereas the right-hand-side plots the percentage change in the price of BITCOINs over time.

6.1. Investor attention and volumes of transactions in BITCOINs on financial markets

We tested our hypotheses by, first of all, looking at the relationship between the volume of BITCOINs transacted on the financial markets and the volume of new financial, technical and

legal information returned to interested investors on Google, upon performing a search query on 'BITCOIN'. Figures 4.7, 4.8 and 4.9 illustrate our findings. The charts show the response of one variable to a shock in the impulse variable. Since we logarithmically transformed the variables, these variations can be interpreted as the reactions to a 10% shock of the impulse variable.

In Figure 4.7, in the first week after a 10% increase in the traded volumes of BITCOIN there was a 1.6% increase in the amount of technical new information that Google returned to its queries. This, in turn, drove a small increase in the transaction volumes. After 2 weeks, the effect of the shock in the traded volumes on new technical information decreased, slightly, to 1.5%. This effect, in turn also caused fewer BITCOIN transactions, and so, after 1 month, the effect of the original shock stabilized. On the long run, there was a 1% increase in the volume of new technical articles on by Google on the BITCOIN query. Figure 4.7 shows that transaction volume shocks reverberated little but significantly with respect to the technical articles that Google returned. Consequently, small shocks to the volume of technical information triggered significantly higher shocks to the volumes of BITCOINs transacted. While these reverberations were strong on the short term, they settled after 4 weeks.

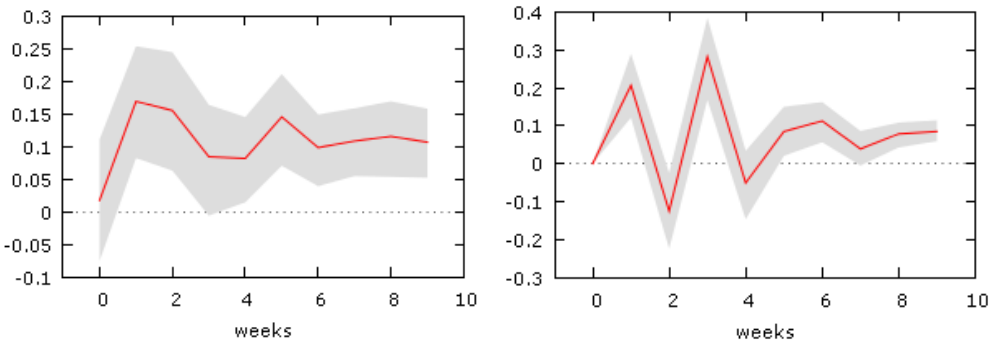

Figure 4.7: Response dynamics: volumes of traded BITCOINs and new technical information using a VECM (3) model, with a 90% confidence band to the point estimates. The left-hand-side chart shows the changes in new technical information returned to potential investors by Google to 10% increase in the traded volume of BITCOINs, and the right-hand-side chart the reverse.

Alternatively, Figure 4.8 depicts the response of the volume of new financial information to a shock in the volume of BITCOINs transacted on financial markets. Financial information was, comparatively, more responsive in the short run, as well as, in the long run. The reaction of the volumes of BITCOINs traded on financial markets to a shock in the volume of financial news returned by Google was, however, smaller, compared to a shock in the volume of technical information. Moreover, as Figure 4.8 showed, financial information reacted more to

changes in the market, than markets did on the basis of new financial information. Finally, it took about 5 weeks for a new equilibrium to be reached.

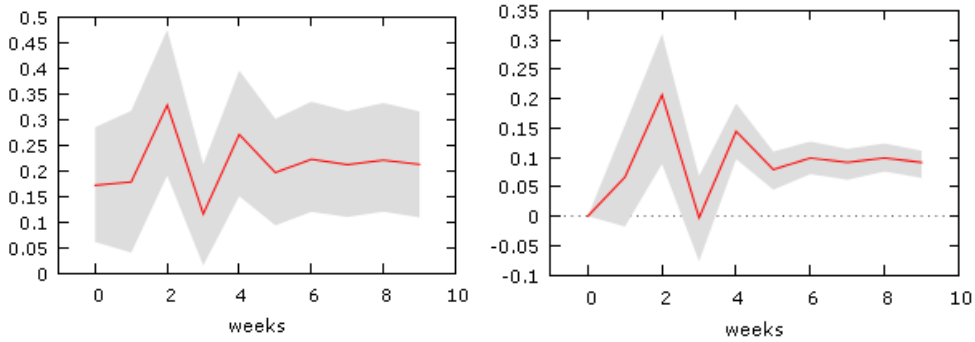

Figure 4.8: Response dynamics: volumes of traded BITCOINs and new financial information, using a VECM (2) model, with a 90% confidence band to the point estimates. The left-hand-side chart shows the changes in new financial information returned to potential investors by Google to 10% increase in the traded volume of BITCOINs, and the right-hand-side chart the reverse.

Our findings did not offer any support for Hypothesis 1, as investors were not able to instantly process novel information. Rather, our findings supported Hypothesis 2 – namely that it takes time to process information, and that this can be seen in the increased trading volatility in the short run that eventually decreases after 1 month. Furthermore, we studied a growing market and it is therefore not surprising that an increase in trading volatility leads to a permanent shift in both financial and technical information. The complete transmission of a 10% increase in market transactions in BITCOINs was a 2% increase in financial information and a 1% increase in technological information. Conversely, the complete transmission of a 10% increase in financial (technological) information was a permanent 1% increase in transactions in BITCOINs.

Figure 4.9 shows that in contrast to financial and technical information, new legal information returned to Google searches did not affect the volume of BITCOINs transacted on financial markets in the long run. In fact, a 10% shock in the volume of legal information generated a short positive significant 1% response in the volume of BITCOINs transacted on financial markets only 3 weeks after the shock. This finding offered support to Hypothesis 3. Not only did investors have limited capacity to solve uncertainty, but they also had limited resource. They thus allocated attention according to priorities.

6.2. *Investor attention and volumes of transactions in BITCOINs outside financial markets*

We then looked at the relationship between the volume of BITCOINs transacted outside financial markets and the volume of new financial, technical and legal information returned to interested investors on Google upon performing a search query on 'BITCOIN'. The volume of BITCOINs transactions recorded in the block-chain that was not affiliated with stock-exchanges responded significantly to new legal information returned by Google on its search queries. As the right-hand side of Figure 4.9 shows, an increase in legal uncertainty caused, in the short run, high volatility in trading outside financial markets. Ownership of BITCOINs changed, at faster rate, in the first week after the shock, and decreased, proportionally, in the second week. Notably, trading on financial markets was only significantly affected in the third week. Finally, the volume of BITCOINs transactions that did not take place on known stock-exchanges was not significantly impacted by the new financial or technological information returned by Google to its queries. We thus found supporting evidence for Hypothesis 3.

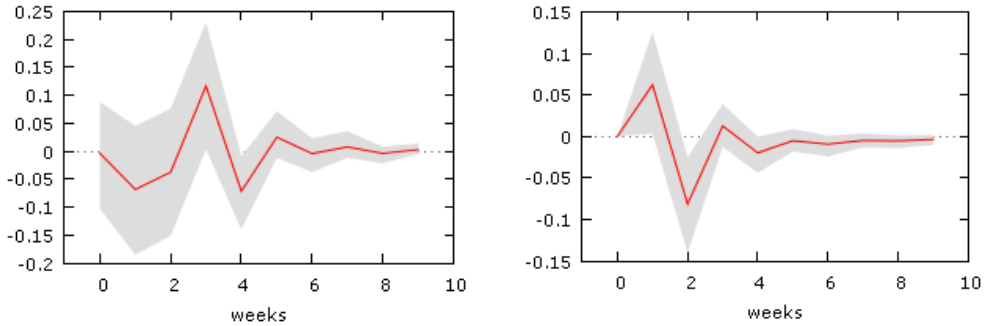

Figure 4.9: Response dynamics: volumes of traded BITCOINs on financial markets and new legal information, using a VAR (3) model, with a 90% confidence band to the point estimates; and volumes of traded BITCOINS outside financial markets and new legal information, using a VAR (2) model, with a 90% confidence band to the point estimates. The left-hand-side chart shows the temporary changes in the traded volume of BITCOINs in response to a 10% shock in the volume of new legal information returned to potential investors by Google. The right-hand-side chart shows the temporary response in the volume of traded BITCOINs outside stock-exchanges to a 10% shock in the volume of new legal information returned to potential investors by Google.

Investor attention and BITCOIN prices

Finally, we explored the extent to which the price of BITCOINs (measured in USD) responded to new information. Since these time series were not cointegrated we employed VAR specifications and found that prices Granger-cause the volume of financial and technological information. Furthermore, we found that shocks to the volume of new legal information had no significant effect on price.

Figure 4.10 reports the relationship between BITCOIN prices and new financial information. Shocks to the volume of new financial information had a significant negative effect on prices only in the first week after the shock. Investors resolved uncertainty within 2 weeks. Consequently, the impact of prices on the volume of new financial information was significantly positive after 2 weeks.

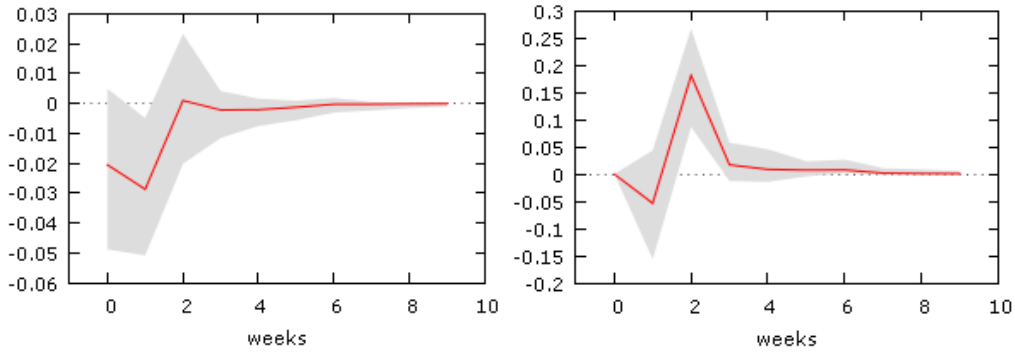

Figure 4.10: Response dynamics: financial information and BITCOIN prices, using a VAR (2) model with a 90% confidence band to the point estimates. The left-hand-side chart shows the temporary changes in BITCOIN prices to a shock in the volume of new financial information returned to potential investors by Google. The right-hand-side chart shows the temporary changes in the volume of new financial information returned to potential investors by Google, to a shock in BITCOIN prices.

Figure 4.11 depicts the relationship between BITCOIN prices and new technological information. Shocks to the volume of new financial information had no significant effect on prices. However, the volume of new technological information reacted to price changes and increased, significantly, 1 week after the shock in prices. Furthermore, prices did not significantly react to legal information and the volume of new legal information did not significantly react to changes in the price of BITCOINs.

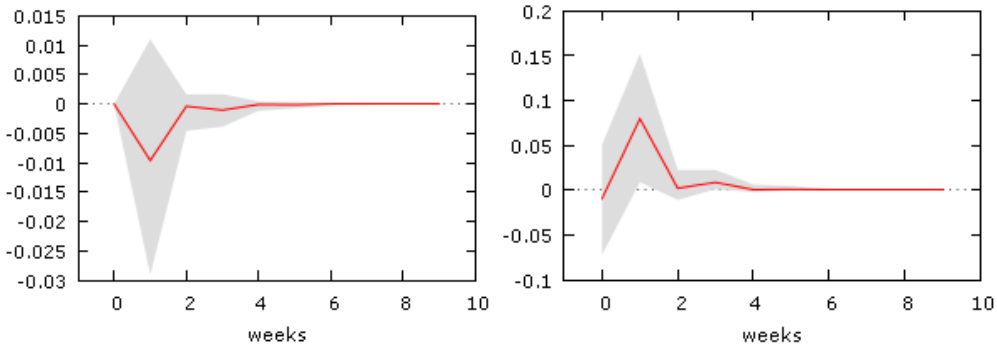

Figure 4.11: Response dynamics: technological information and BITCOIN prices, using a VAR (2) model with a 90% confidence band to the point estimates. The left-hand-side chart shows the temporary changes in BITCOIN prices to a shock in the volume of new technological information returned to potential investors by Google. The right-hand-side chart shows the temporary changes in the volume of new technological information returned to potential investors by Google, to a shock in BITCOIN prices.

Our results are in line with the findings of Buchholz *et al.* (2012). They showed that Google trends Granger caused the number of BITCOIN transactions in the short run but not in the long run. Furthermore, the separation we made between volumes of transactions that take place on and outside financial markets brought us to similar conclusions to those of Glaser *et al.* (2014). They showed that Wikipedia trends explained changes in transactions volumes on financial markets but did not explain changes in transaction volumes outside financial markets nor in BITCOIN prices. Our results were also in line with those of Kristoufek (2013) who showed that Google trends significantly responded to a price shock in the first two weeks after the shock. Finally, we found that the magnitude of the response of Google trends to BITCOIN price change was very close to that of Kristoufek (2013).

Importantly, our contribution laid in the development of a novel measure for investor attention that was in line with the earlier employed Google and Wikipedia trends but that was richer in information about the true nature of the investor's intent and that was more transparent by design. With this method we was able, in a primer, to distinguish to which information various clusters of BITCOIN users dedicated attention to when having limited attention. We could thus see that technology news was followed by both traders and by parties that transacted in BITCOINs, a likely consequence of the advanced cryptographic features of BITCOINs. Furthermore, we found that legal information was prioritized by (legal and illegal) businesses trading in BITCOINs whereas financial information was prioritized by speculators only.

6.3. Sources of information that have an effect

Most information published on BITCOINs is not centralized. The granularity shown in Figure 4.4 suggests that a better approach to distilling the main sources of information for BITCOIN investors is the functional taxonomy introduced in Section 4.2. Figure 4.12 presents the main sources that have contributed to each proxy. One third of technological information originated from websites with an explicit technical profile, 24% from forums and 18% from blogs. Similarly, one third of financial information originated from financial websites, 28% from news articles and less than 20% from blogs. Blogs and news however accounted for 79% of legal information.

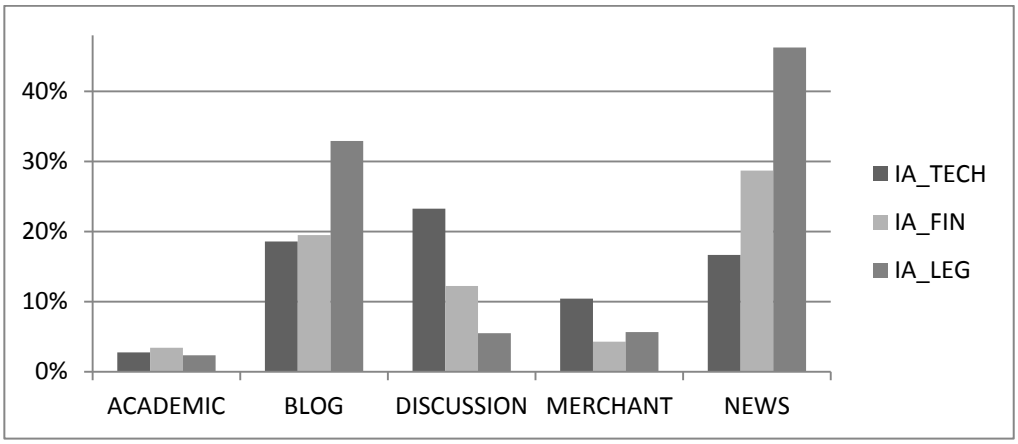

Figure 4.12: Sources of technological, financial and legal information returned by Google to the query 'BITCOIN' and their contribution (as % of total information returned by Google).

Figure 4.12 points to the fact that speculators and miners to whom technological and financial information was most relevant, paid attention to information about BITCOINs that was published in the news, on blogs and on websites having a specialized financial or technological profile. Conversely, users mostly got informed from blogs and news on technological and legal information. This in turn suggests that Google and Wikipedia trends may be further refined by looking at the frequency with which these sources were visited instead of counting the overall number of queries.

7. Conclusion

We began this chapter by noting that BITCOINs proposed several paradigm changes and challenged some of the fundamentals of modern finance. Although they proposed a higher degree of individual anonymity, systemic transparency and lower transaction costs, by taking the world by surprise, they generated instability, developed in an ambiguous regulatory framework and consequently, triggered opportunistic and frightening thoughts among their stakeholders. We then introduced the notion that stakeholders' perceptions over the opportunities and threats that BITCOINs may entail were actually the driving forces behind BITCOINs. If perceptions were good BITCOINs would survive, if they were bad, BITCOINs would fail. But what if they were both good and bad?

Importantly, our perspective suggested that financial markers – *i.e.* prices and volumes of transactions in BITCOINs on the stock exchange – as well as volumes of trade in BITCOINs significantly depended on the perceptions stakeholders had on BITCOINs. Specifically, BITCOIN stakeholder would form their perceptions in relation to what they knew about BITCOINs and would then decide which course of action to take. Consequently, studying stakeholders' "wisdom of the crows" on BITCOINs could help understand their perceptions and therefore explain their trade reactions. This view is in line with contemporary research, which showed that the number of searches on Google (and on Wikipedia) for the keyword "BITCOIN" was able to explain BITCOIN price volatility and transaction volumes volatility (Buchholz *et al.* 2012; Kristoufek, 2013). Similarly, it is in line recent research showing that an analysis of the search patterns associated to the query "BITCOIN" in Google was able to place stakeholders' interest in a better context and could reveal the identity of stakeholders (Yelowitz & Wilson, 2015).

Our approach was based on a synthesis of the existing debate on BITCOINs. This synthesis allowed us to capture the main dynamics between opportunities and threats and to place them in a context. We found that there were three major debating contexts: a financial, a legal and a technological context. In each of these three, threats and opportunities were constantly being exposed, analyzed and somewhat discarded, in what constituted a tumultuous spectacle to the majority of BITCOIN investors. We applied this framework for analysis to a random sample of information available to English speaking stakeholders that queried for "BITCOIN" from 2010 to 2014. Importantly, this was a random sample selected from the equilibrium path of information – *i.e.* information that is supplied and revealed to Google interested users at a specific moment in time. In other words, our perspective emphasized the need to go further than using Google and Wikipedia trends as they are only measures of the demand for information about BITCOINs but no measure for the nature of information searched and found.

In terms of implications for the investment attention literature, such a methodological change would allow us to progress in understanding investment attention and its impact on financial markets. The case of BITCOINs was a good starting point, as all transactions in BITCOINs are registered in a block-chain in real time, such that all that needs to be mapped on top of this perfectly robust record of transactions was the discussions and attention paying stakeholders. In terms of implications for the money laundering literature, with a good map of discussions and an impeccable recorded history, one would be able to achieve more financial transparency and even considerably reduce the information asymmetry between money launderers and law enforcement agencies.

This chapter took the first steps in this direction by distilling from the sample of Google discussions those that belong to the financial, the legal or the technological field. We were able to do so by using grounded theory as proposed by Glaser and Strauss (1967). Importantly, given the size of the volume of discussions incorporated in our sample, we automated the data analysis such that texts were classified into one or more of the aforementioned fields if they contain a set of key semantic codes. These codes have been designed following the methods proposed by Miles and Huberman (1994) – *i.e.* in consultation with colleagues and experts and on the basis of a subset of articles read by three human experts.

Equipped with three daily measures of new information (legal, financial and technological), we followed the econometric explorations of Kristoufek (2013) and of Glaser *et al.* (2014). The block-chain record of transactions and the record of transactions kept by stocks exchanges allowed us to separate a special third measure: the volume of transactions in BITCOINs that were not recorded by stock-exchanges – *i.e.* transactions that took place outside the financial markets. The latter were the equivalent of the velocity of cash outside the monitoring eye of the banking sector, with the notable exception that the BITCOIN velocity was recorded.

We then posited three hypotheses. These hypotheses reflected opposing beliefs on investors' attention and the impact investor's attention had on financial markets. The first Hypothesis reflected standard asset pricing theories that assert that financial markets can perfectly incorporate new information into prices and transaction volumes. The second and third Hypothesis reflected behavioural assumptions on financial performance that assert that investors have limited capacity to resolve uncertainty, and, respectively, that they also have limited resources to allocate to resolving uncertainty (*cf*. Peng *et al.*, 2007). Assuming a positive correlation between absolute price changes and transaction volumes (*Cf*. Kristoff, 1987), our empirical results supported the third Hypothesis, namely that investors had limited capacity to solve their uncertainty in relation to BITCOINs and moreover limited resources to allocate to resolving uncertainty. Notably, our three measures allowed us to distinguish which information was prioritized by each of them and the impact thereof. We found, for the first

time, evidence that all BITCOIN stakeholders were interested in the technological news, a likely consequence of the advanced cryptographic features of BITCOINs. Furthermore, we found that speculators paid attention to financial information, our only proxy that significantly correlated with the earlier used Google trends. Therefore, our results with respect to the behaviour and interest of speculators approached those already expressed by the literature. We nevertheless, contributed by adding the legal information proxy which was only prioritized by (legal and illegal) businesses trading in BITCOINs. The final great benefit of our method is that we were able to additionally identify the sources of information that were prioritized by each of these groups. Miners and speculators essentially paid attention to technological and financial dedicated sources, to the news and to blogs. This raises the question whether Google trends can continue to be used as accurate measurement of the interest of these groups of BITCOIN investors. One could imagine that a more accurate analysis of investor sentiment could be done using individual discussion forums dedicated to BITCOINs – such as Reddit or Coindesk.

Finally, and more generally, our findings showed that the way forward is to use economic, management and computer science perspectives and theories in the exploration of who stands behind BITCOINs and why. As North (1994, pp.362-363) stated: "feedback derived from new experiences […] sometimes strengthens our initial categories and models, or may lead to modification—in short, learning". We hope our attempt will create momentum for additional research on what BITCOIN stakeholders learned, both at a collective and at an individual level, from talking about BITCOINs, and how this impacted their financial choices.

Appendices

Appendix – Chapter 1

Table A1.1: OLS of the cash to currency ratio in the Eurozone according to Tanzi's CDA specification.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wage/GDP	-0.475***	-0.528***	-0.358***	-0.361***	-0.0705	0.0954	-0.395***	-0.377***
	(-5.38)	(-4.22)	(-4.86)	(-4.82)	(-0.68)	(0.71)	(-5.49)	(-6.09)
Interest rate	-0.0356	-0.118	-0.0431	-0.0617	-0.104**	-0.181***	-0.165***	-0.119***
	(-0.73)	(-1.92)	(-1.22)	(-1.85)	(-3.39)	(-9.01)	(-9.07)	(-6.13)
GDP per capita	2.143***	2.386***	1.687***	1.688***	0.680*	0.117	2.050***	1.943***
	(22.59)	(12.02)	(16.94)	(16.59)	(2.36)	(0.28)	(26.59)	(28.65)
Tax wo SSC/GDP	-3.985***							
	(-4.40)							
Tax woSSC/TT		-6.209						
		(-2.06)						
Income tax/GDP			-2.546***					
			(-6.01)					
Income tax/TT				-3.302***				
				(-5.82)				
Labour tax paid by employees/GDP					-3.425***			
					(-5.01)			
Labour tax paid by employees/TT						-5.380***		
						(-4.71)		
Labour tax paid by employers/GDP							2.746***	
							(6.19)	
Labour tax paid by employers/ TT								2.017***
								(7.74)
_cons	-6.002	5.148	-9.741***	-5.153*	0.150	13.80	-21.74***	-21.51***
	(-2.06)	(0.45)	(-6.28)	(-2.19)	(0.04)	(2.00)	(-30.38)	(-37.57)
Observations	28	28	28	28	28	28	28	28
Adjusted R^2	0.965	0.945	0.975	0.974	0.969	0.967	0.976	0.982

Notes. t statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table A1.2: First difference OLS of the cash to currency ration in the Eurozone according to Tanzi's specification.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D. Wage/GDP	-0.335*	-0.334*	-0.331*	-0.332*	-0.311*	-0.295*	-0.316*	-0.319*
	(-2.79)	(-2.65)	(-2.81)	(-2.79)	(-2.66)	(-2.46)	(-2.57)	(-2.69)
D. Interest rate	-0.0780	-0.0990	-0.0831	-0.0879	-0.112*	-0.151**	-0.120*	-0.0991
	(-1.30)	(-1.52)	(-1.50)	(-1.59)	(-2.32)	(-3.16)	(-2.35)	(-1.90)
D. GDP per capita	1.820***	1.826**	1.805***	1.811***	1.743***	1.696**	1.766**	1.77***
	(3.92)	(3.75)	(3.95)	(3.93)	(3.84)	(3.65)	(3.71)	(3.85)
D. Tax wo SSC/GDP	-2.420							
	(-1.72)							
D. Tax wo SSC/TT		-3.531						
		(-0.98						
D. Income tax/GDP			-1.688					
			(-1.95)					
D. Income tax/TT				-2.198				
				(-1.82)				
D. Labour tax paid by employees/GDP					-2.596			
					(-2.01)			
D. Labour tax paid by employees/TT						-4.236		
						(-1.76)		
D. Labour tax paid by employers/GDP							1.889	
							(1.31)	
D. Labour tax paid by employers/TT								
1.682								
								(1.84)
_cons	0.000594	0.000569	-0.000947	-0.00118	-0.00584	-0.00898	0.000982	0.00110
	(0.12)	(0.11)	(-0.20)	(-0.25)	(-1.08)	(-1.32)	(0.19)	(0.23)
Observations	27	27	27	27	27	27	27	27
Adjusted R^2	0.546	0.506	0.561	0.552	0.565	0.548	0.522	0.553

Notes. t statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table A1.3: US data adapted from Tanzi (1983) and updated until 2006.

Year	C	M2	T	Y	WS/NI	R
1929	3,64	46,60	4,04	2,58	59,50	3,34
1930	3,37	49,70	2,63	2,31	62,62	3,31
1931	3,65	42,70	1,81	2,11	66,83	2,99
1932	4,62	36,10	2,83	1,81	71,96	2,80
1933	4,76	32,20	3,40	1,76	72,76	2,56
1934	4,65	34,40	4,00	1,89	69,26	2,37
1935	4,78	39,10	4,41	2,04	64,99	1,93
1936	5,22	43,50	6,31	2,30	65,24	1,64
1937	5,49	45,70	5,38	2,39	63,82	1,55
1938	5,42	45,50	4,05	2,28	65,17	1,48
1939	6,01	49,30	4,00	2,43	64,52	1,36
1940	6,70	55,20	4,09	2,59	62,56	1,22
1941	8,20	62,50	6,63	2,98	60,52	1,12
1942	10,90	71,20	11,32	3,40	60,50	1,03
1943	15,81	89,90	14,65	3,87	62,44	0,87
1944	20,88	106,80	13,89	4,10	64,29	0,84
1945	25,10	126,60	14,17	3,99	65,05	0,85
1946	26,52	139,00	11,97	3,36	62,84	0,82
1947	26,60	146,00	12,03	3,23	63,25	0,85
1948	26,00	147,80	9,41	3,31	61,87	0,87
1949	25,60	147,70	9,01	3,27	63,36	0,90
1950	25,10	151,00	10,22	3,49	62,24	0,92
1951	25,40	155,50	11,93	3,72	62,90	1,02
1952	26,70	164,50	12,87	3,80	64,86	1,14
1953	27,70	171,10	12,80	3,88	66,27	1,30
1954	27,50	176,70	11,58	3,76	65,80	1,30
1955	27,60	183,60	11,78	3,95	64,54	1,36
1956	27,90	186,70	12,19	3,96	65,83	1,58
1957	28,30	191,70	12,23	3,96	66,04	2,08
1958	28,30	201,60	12,17	3,89	66,07	2,20
1959	29,00	211,00	12,60	4,05	64,61	2,36
1960	29,00	210,80	12,47	4,08	65,41	2,58
1961	28,90	223,40	12,76	4,11	65,17	2,73
1962	30,00	236,60	12,83	4,28	64,51	3,23
1963	31,50	251,40	13,02	4,39	64,15	3,34
1964	33,50	266,40	11,84	4,56	64,04	3,47
1965	35,00	287,40	11,50	4,77	63,24	3,73
1966	37,00	312,10	11,93	4,99	63,43	4,12
1967	39,00	335,10	12,42	5,07	64,48	4,32
1968	41,80	364,00	13,78	5,24	65,00	4,36
1969	44,70	391,80	14,30	5,32	66,17	4,57
1970	47,60	402,80	13,26	5,25	67,68	4,98
1971	51,00	454,80	12,65	5,35	66,66	4,77
1972	54,30	498,00	12,52	5,61	65,92	4,62
1973	59,20	548,10	13,04	5,96	67,69	5,82
1974	64,50	594,20	13,64	5,89	65,97	7,14
1975	71,00	642,20	13,13	5,78	65,06	5,96
1976	77,70	698,20	13,36	6,04	64,52	5,32
1977	84,30	775,50	13,68	6,32	63,61	5,24
1978	92,80	840,60	14,33	6,57	63,32	5,87
1979	101,80	915,50	14,56	6,72	61,96	7,41
1980	111,00	982,60	15,51	6,65	63,34	8,52
1981	118,95	1254,69	16,09	12,55	55,37	15,91
1982	127,76	1379,95	14,81	13,80	55,68	12,04
1983	140,09	1553,70	13,83	15,54	54,65	8,96
1984	152,01	1682,56	13,75	16,83	53,30	10,17
1985	162,29	1831,78	13,83	18,32	53,64	7,97
1986	174,28	1949,22	14,54	19,49	54,30	6,61
1987	188,61	2042,28	13,12	20,42	54,37	6,74
1988	205,06	2161,30	13,21	21,61	53,95	7,59
1989	217,33	2277,37	13,12	22,77	53,81	9,11
1990	235,07	2416,82	12,95	24,17	54,18	8,15
1991	259,00	2488,11	12,75	24,88	53,94	5,82
1992	279,13	2443,67	12,94	24,44	53,89	3,64
1993	307,85	2367,32	13,32	23,67	53,18	3,11
1994	340,74	2347,78	13,50	23,48	52,27	4,38
1995	366,79	2422,56	13,86	24,23	52,41	5,87
1996	382,32	2631,46	14,34	26,31	52,17	5,35
1997	409,99	2853,58	14,48	28,54	52,34	5,54
1998	442,15	3124,73	14,42	31,25	53,09	5,49
1999	486,34	3413,14	14,85	34,13	53,36	5,19
2000	522,77	3681,45	15,26	36,81	54,01	6,35
2001	555,01	4061,89	14,23	40,62	53,91	3,82
2002	608,95	4403,08	13,03	44,03	53,12	1,72
2003	647,64	4711,81	11,90	47,12	52,24	1,15
2004	680,67	4918,15	12,10	49,18	51,51	1,45
2005	710,10	5155,11	12,45	51,55	50,57	3,34
2006	740,12	5480,92	12,60	54,81	50,44	5,06

Table A1.4: Eurozone quarterly data – cash to money supply ratio, tax rates, income per capita, interest rate and wages and salaries paid in cash.

	M1/M3	T1	T2	T3	T4	T5	T6	T7	T8	Y/N	R	WS
2002Q01	0.06	26.61	66.38	9.76	23.94	7.98	19.78	10.71	26.62	5721.6	3.34	89.84
2002Q02	0.06	26.53	66.25	9.71	23.83	7.99	19.82	10.69	26.59	5883.4	3.36	100.23
2002Q03	0.06	26.44	66.12	9.65	23.71	8.00	19.87	10.66	26.57	5879.2	3.34	92.67
2002Q04	0.06	26.36	65.99	9.59	23.60	8.01	19.92	10.63	26.55	6082.3	3.17	104.39
2003Q01	0.06	26.27	65.86	9.54	23.49	8.02	19.97	10.61	26.52	5828.1	2.74	91.05
2003Q02	0.06	26.18	65.73	9.48	23.38	8.03	20.02	10.58	26.50	5987.6	2.43	101.52
2003Q03	0.07	26.09	65.66	9.42	23.27	8.02	20.04	10.52	26.42	6011.3	2.13	93.55
2003Q04	0.07	25.98	65.65	9.34	23.16	7.98	20.03	10.42	26.28	6218.9	2.11	105.45
2004Q01	0.07	25.88	65.65	9.26	23.06	7.95	20.02	10.32	26.13	6033.1	2.06	92.98
2004Q02	0.07	25.77	65.65	9.18	22.96	7.92	20.02	10.22	25.99	6212.3	2.06	103.18
2004Q03	0.07	25.74	65.67	9.15	22.92	7.90	20.00	10.16	25.90	6211.4	2.08	95.02
2004Q04	0.08	25.78	65.72	9.17	22.94	7.90	19.97	10.15	25.84	6447.4	2.12	107.10
2005Q01	0.08	25.82	65.77	9.18	22.97	7.89	19.94	10.14	25.79	6186.6	2.11	93.16
2005Q02	0.08	25.86	65.82	9.20	22.99	7.89	19.91	10.13	25.74	6434.2	2.10	102.99
2005Q03	0.08	25.94	65.91	9.22	23.01	7.88	19.85	10.12	25.67	6394.0	2.11	95.51
2005Q04	0.08	26.06	66.04	9.25	23.03	7.87	19.77	10.10	25.57	6660.2	2.25	108.33
2006Q01	0.08	26.18	66.16	9.28	23.05	7.86	19.68	10.09	25.48	6482.0	2.49	96.23
2006Q02	0.08	26.30	66.29	9.31	23.07	7.85	19.60	10.07	25.38	6693.6	2.74	106.43
2006Q03	0.08	26.40	66.41	9.35	23.12	7.85	19.55	10.07	25.32	6684.6	3.06	98.54
2006Q04	0.08	26.49	66.50	9.40	23.21	7.86	19.54	10.07	25.29	6946.5	3.47	111.96
2007Q01	0.08	26.57	66.60	9.44	23.30	7.87	19.52	10.07	25.27	6805.7	3.71	101.30
2007Q02	0.08	26.66	66.70	9.49	23.39	7.87	19.51	10.07	25.24	6992.4	3.96	110.33
2007Q03	0.08	26.75	66.80	9.54	23.48	7.88	19.49	10.07	25.21	6951.6	4.28	102.95
2007Q04	0.08	26.83	66.90	9.59	23.56	7.89	19.48	10.07	25.18	7214.3	4.39	116.47
2008Q01	0.08	26.92	66.99	9.64	23.65	7.90	19.46	10.08	25.16	7045.3	4.23	104.78
2008Q02	0.08	27.01	67.09	9.69	23.74	7.90	19.45	10.08	25.13	7229.9	4.41	113.51
2008Q03	0.08	27.09	67.18	9.74	23.83	7.91	19.44	10.08	25.10	7120.2	4.54	105.76
2008Q04	0.08	27.18	67.27	9.78	23.92	7.92	19.42	10.08	25.08	7224.6	3.89	105.99

Table A1.5: Sources of the Eurozone and US data.

Sources for the European data in Table A1.4
Money supply (M_1, M_3): European Central Bank: http://sdw.ecb.europa.eu/ **Tax data (T_1, T_2, T_3, T_4 T_5 T_6 T_7 T_8): The European Commission Taxation and Customs Union report 2009 Report: http://epp.eurostat.ec.europa.eu/portal/page/portal/national_accounts/data/database** **Interest rates (R), income per capita (Y/N) and wages and salaries to national income (WS/Y): Eurostat: http://epp.eurostat.ec.europa.eu/portal/page/portal/interest_rates/data/database**
Sources for US data in Table A1.3
Money supply (C, M_2) and interest rate (R): Federal Reserve Bank Data: www.federalreserve.gov/releases/h6/hist/h6hist2.txt (M1 and M0 in the US 1975 –Aug 2009), www.federalreserve.gov/releases/h6/hist/h6hist1.txt (M1 and M2 in the US 1975 –Aug 2009), www.federalreserve.gov/releases/h6/hist/h6hist5.txt (M2-M1 as in Tanzi), www.federalreserve.gov/releases/h15/data.htm#top (monthly interest on 1-month CDs)
Income per capita (Y/N): Penn World Table: http://pwt.econ.upenn.edu/php_site/pwt63/pwt63_form.php
Wages and Salaries to personal disposable income per capita (WS/NI): U.S. Department of Commerce, Bureau of Economic Analysis: www.bea.gov/national/nipaweb/TableView.asp?SelectedTable=58&ViewSeries=NO&Java=no&Request3Place=N&3Place=N&FromView=YES&Freq=Qtr&FirstYear=1975&LastYear=2009&3Place=N&Update=Update&JavaBox=no#Mid Transforming the real income per capita data in 2005 US$ into 1972 US$ terms has been done using an inflation calculator, the method and the program easily downloadable at: http://inflationdata.com/Inflation/Inflation_Calculators/Inflation_Rate_Calculator.asp
Tax data (T): Internal Revenue Service: www.irs.gov/taxstats/indtaxstats/article/0,,id=96679,00.html#_grp8

Appendix – Chapter 2

Appropriate measures association: Pearson, Spearman rank and Kendall rank correlations

In the course of time, statisticians have developed several measures of association – from Pearson's correlation, to rank correlation, maximal linear correlation and the more recent distance correlation, each with their limitations (Speed, 2011; De Siqueira Santos, Takahashi, Nakata & Fujita, 2013). Pearson's correlation coefficient, as introduced by Pearson (1895), $r = \frac{\mathrm{cov}\ (\mathrm{X,Y})}{\sigma_{\mathrm{X}}\sigma_{\mathrm{Y}}}$ is one of the most common measures for the degree of association between two sets of variables X and Y. However, this measure is sensitive to heavy-tailed distributions of the variables in question, which was the case in my dataset. Moreover, I had little reason to believe that the relationship between my measure of effective information sharing and the rate at which Member States combat money laundering is linear. Thus, I considered two additional measures of association: Spearman's rank correlation and Kendall's tau rank correlation.

Spearman (1904) measured how well the relationship between two variables can be described using a monotonic function. Spearman's rank correlation coefficient measures thus, the extent to an increase in X translates into an increase in Y. Spearman's coefficient measures the distance between the ranked variables, $\rho = \frac{6\sum(x-y)^2}{n(n^2-1)}$, where x and y and n are the ranked variables X and Y and the sample size, respectively. Spearman's correlation index is a more appropriate measure of association when the two variables are not normally distributed.

Similarly, Kendall (1938) measured the degree of association between variables X and Y by pairing observations (x_i, y_i) according to their rank and counting how many pairs are both larger (or smaller) than the next one. Pairs that are both larger are called concordant. Pairs where only one is larger and the other is smaller are called discordant. Kendall's rank correlation coefficient thus measures to what extent concordant pairs are more present than discordant pairs $\tau = \frac{(numberofconcordantpairs)-(numberofdiscordantpairs)}{\frac{1}{2}n(n-1)}$. Although Kendall's measure is used mostly with small samples (*Cf*. Colwell & Gillet, 1982; Xu, Hou, Hung & Zou 2010), the differences between the two rank estimates was not seen as important for the purpose of this exercise.

Table A2.1: Information dispersion amplitude given the information sharing type and the presence of liaison officers, threat of money laundering population per EU Member State.

	Information dispersion amplitude[a]	Information sharing type	Liaison officer[b]	ML threat (in bln Euro)[c]	Population (millions)
AT	18.11	Police	No	89	8.4
BE	21.10	Linear	Yes	120	10.8
BG	13.84	Linear	No	19	7.5
CY	15.69	Judicial	Yes	19	0.8
CZ	20.56	Star	No	51	10.5
DK	18.06	Judicial	Yes	59	5.6
EE	15.34	Police	No	40	1.3
FI	16.01	Police	No	45	5.4
FR	20.74	Linear	Yes	151	65.4
DE	17.27	Police	No	109	81.5
EL	17.44	Linear	Yes	17	11.3
HU	16.84	Star	No	20	10.0
IE	16.60	Police	No	54	4.5
IT	15.63	Star	No	74	60.5
LV	12.61	Judicial	No	43	2.2
LT	13.29	Police	No	13	3.3
LU	16.71	Judicial	Yes	94	0.5
MT	21.19	Linear	Yes	8	0.4
NL	24.23	Star	Yes	94	16.6
PL	16.34	Star	No	54	38.1
PT	15.21	Police	No	43	10.6
RO	12.81	Linear	No	14	21.5
SK	13.81	Police	No	24	5.4
SL	18.78	Star	No	35	2.1
ES	20.09	Linear	Yes	56	46.1
SE	19.35	Police	No	26	9.4
UK	17.31	Police	No	282	61.8

Notes. [a] based on own calculations; [b] adapted from ECOLEF (2013, p.43); [c] adapted from ECOLEF (2013, p.509).

Table A2.2: Average number of prosecutions, convictions and persons involved in them, between 2008 and 2010.

	Avg. Convictions [d]	Avg. Sentences [ab]	Avg. Persons [a]	Avg. Prosecutions [a]	Avg. suspicion reports[c]
AT	14.8	14.3	15.3	22.5	1554.0
BE	1274.3		1274.3	1432.7	17132.3
BG	24.5	16.0	33.0	186.7	978.0
CY	16.3	19.0	13.7	38.3	399.0
CZ	390.3			38.3	2143.7
DK	506.0	506.0		534.0	1988.0
EE	18.3	9.3	27.3	26.0	5713.7
FI	22.8	23.3	22.3	76.3	23995.7
FR	282.8	198.5	367.0	225.0	15937.5
DE	576.0	576.0	576.0	14027.7	9145.7
EL	34.0	34.0		42.0	2152.7
HU	9.0	9.0	9.0	5.7	7512.7
IE	4.4	4.3	4.5	4.0	24437.2
IT	1328.3	1862.3	794.3	1482.0	24329.7
LV	17.3	17.3	17.3	57.3	26959.7
LT	1.0	1.0	1.0	7.7	208.3
LU	11.2	3.0	19.3	59.7	2294.0
MT	2.3	2.7	2.0	5.5	67.3
NL	729.5	729.5		893.0	245390.0
PL	39.3	22.5	56.0	69.5	1891.3
PT	11.3	11.3	11.3	137.0	1110.0
RO	2.0	2.0	2.0	419.0	2862.0
SK	10.8	10.3	11.3	66.0	2451.7
SL	0.8	1.0	0.7	15.0	205.3
ES	95.3	126.7	64.0	160.0	2946.7
SE	62.3	62.3	62.3	61.3	11092.5
UK	1411.0	1411.0		2330.0	224798.5

Notes. [a] adapted from ECOLEF (2013, pp.501-505) and, where data was missing, completed from Eurostat (2013, pp.55-64), from what was reported under the headings: *'Number of sentences by type for money laundering offences'* and *'Number of persons / legal entities convicted for money laundering offences'* and *'Number of cases brought to prosecution: originating from STRs, CTRs and independent law enforcement investigation'* respectively; [b] given the different interpretations given to the notions *'sentence for money laundering'* and *'convictions for money laundering'* across countries and between the databases, we kept to the ECOLEF (2013) study and report significant discrepancies for Cyprus, Czech Republic,

Estonia, France, Hungary, Latvia, Lithuania, the Netherlands, Poland and Slovakia; [c] adapted from ECOLEF (2013, p.496); [d] reports the average between data on *'Avg. Sentences'* and *'Avg. Persons'.*

Table A2.3: Robustness checks – Pearson correlation between the information dispersion amplitude measure and different measures of effective repression of money laundering, using the entire sample and by sequentially discarding data of one Member State.

	Avg. convictions	Avg. persons convicted or prosecuted	Convictions per bln of threat	Convictions per mln inhabitants	Persons convicted or prosecuted per suspicion report	Suspicion reports
ALL MS	0.333*	0.369*	0.33*	0.409**	0.407*	0.36*
w/o AT	0.342*	0.385*	0.341*	0.4189**	0.422*	0.367*
w/o BE						0.381*
w/o BG				0.4**	0.468**	0.353*
w/o CY				0.415**	0.43*	0.355*
w/o CZ		0.369*		0.39**	0.407*	0.389**
w/o DE	0.336*	0.371*	0.331*	0.41**	0.44**	0.36*
w/o DK		0.369*		0.447**	0.407*	0.366*
w/o EE				0.41**	0.397*	0.356*
w/o EL	0.336*	0.369*	0.331*	0.413**	0.407**	0.363*
w/o ES	0.355*	0.404*	0.348*	0.441**	0.413*	0.383*
w/o FI				0.405**	0.404*	0.362*
w/o FR	0.334*		0.352*	0.445**	0.414*	0.379*
w/o HU	0.332*	0.372*		0.409**	0.416*	0.36*
w/o IE	0.33*	0.37*		0.407**	0.413*	0.361*
w/o IT	0.446**	0.457**	0.575***	0.416**	0.428*	0.363*
w/o LT				0.395**	0.386*	0.353*
w/o LU	0.331*	0.37*		0.411**	0.409*	0.359*
w/o LV				0.412**	0.371*	0.383*
w/o MT	0.382*	0.443**	0.38*	0.449**	0.391*	0.399**
w/o NL		0.369*		0.369*	0.407*	
w/o PL				0.406**	0.414*	0.357*
w/o PT				0.4**	0.4*	0.354*
w/o RO				0.395**	0.372*	0.357*
w/o SK				0.398*	0.387*	0.355*

w/o SL	0.35*	0.395*	0.349*	0.427**	0.448**	0.372*
w/o SE	0.351*	0.394*	0.337*	0.425**	0.453**	0.371*
w/o UK	0.387*	0.369*	0.331*	0.41**	0.407*	0.47**

Notes. Only significant correlations are reported; *p< .1, **p< .05, ***p< .01.

Table A2.4: Robustness checks – Spearman rank correlation between the information dispersion amplitude measure and different measures of effective repression of money laundering, using the entire sample and by sequentially discarding data of one Member State.

	Avg. convictions	Avg. sentences	Threat in bln of Euro	Convictions per suspicion report	Convictions per bln of threat	Convictions per mln inhabitants	Sentences per bln of threat	Persons convicted or prosecuted per suspicion report
ALL MS	0.399	0.341	0.414	0.393	0.415	0.382	0.341	0.385
w/o AT	0.432	0.371	0.402	0.405	0.465	0.416	0.403	0.391
w/o BE	0.362	0.341	0.371	0.345	0.372		0.341	
w/o BG	0.395		0.38	0.43	0.419	0.378	0.347	0.466
w/o CY	0.403		0.397	4.421	0.419	0.414	0.342	0.443
w/o CZ	0.372	0.341	0.413	0.35	0.378		0.341	0.385
w/o DE	0.398		0.418	0.389	0.409	0.396		
w/o DK	0.396		0.409	0.385	0.416	0.372		0.385
w/o EE	0.389		0.406	0.374	0.408	0.413		0.369
w/o EL	0.388		0.462	0.389	0.406	0.398		0.385
w/o ES	0.371		0.399	0.37	0.39	0.406		
w/o FI	0.396		0.4	0.38	0.419	0.389	0.345	0.392
w/o FR	0.372		0.371	0.395	0.393	0.389		
w/o HU	0.412	0.358	0.424	0.391	0.418	0.394		0.41
w/o IE	0.411	0.359	0.409	0.403	0.427	0.383	0.356	0.433
w/o IT	0.473	0.413	0.434	0.442	0.498	0.414	0.416	0.447
w/o LT	0.347		0.368	0.372	0.365			
w/o LU	0.406	0.359	0.424	0.387	0.427	0.387	0.363	0.387
w/o LV	0.406	0.357	0.425	0.328		0.408	0.454	
w/o MT	0.514	0.456	0.569	0.374	0.496	0.398	0.401	
w/o NL	0.348		0.367	0.495	0.365			0.385
w/o PL	0.397		0.409	0.416	0.419	0.383	0.348	0.418

w/o PT	0.383		0.405	0.407	0.395	0.352		0.401
w/o RO	0.347		0.368		0.378			
w/o SK	0.374		0.387	0.372	0.408	0.359		
w/o SL	0.482	0.44	0.453	0.432	0.497	0.439	0.443	0.438
w/o SE	0.371		0.453	0.404	0.389	0.389		0.399
w/o UK	0.406		0.43	0.395	0.409	0.371		0.385

Note. Only significant correlations (*p< .1) are reported.

Table A2.5: Robustness checks – Kendall rank correlation between the information dispersion amplitude measure and different measures of effective repression of money laundering, using the entire sample and by sequentially discarding data of one Member State.

	Avg. convictions	Avg. sentences	Threat in bln Euro	Convictions per suspicion report	Convictions per bln of threat	Convictions per mln inhabitants	Persons convicted or prosecuted per suspicion report
ALL MS	0.299	0.243	0.316	0.282	0.299	0.276	0.303
w/o AT	0.323	0.265	0.311	0.292	0.335	0.298	0.309
w/o BE	0.268	0.243	0.286	0.249	0.261		
w/o BG	0.305		0.289	0.311	0.311	0.274	0.367
w/o CY	0.305		0.308	0.317	0.305	0.298	0.338
w/o CZ	0.28	0.243	0.323	0.255	0.268	0.237	0.303
w/o DE	0.305		0.317	0.208	0.298	0.292	0.29
w/o DK	0.305		0.317	0.28	0.298	0.268	0.303
w/o EE	0.292		0.311	0.274	0.286	0.292	0.295
w/o EL	0.286		0.354	0.28	0.292	0.292	0.303
w/o ES	0.274		0.311	0.261	0.286	0.292	0.281
w/o FI	0.292		0.298	0.274	0.298	0.286	0.309
w/o FR	0.208		0.286	0.28	0.292	0.28	0.281
w/o HU	0.317	0.257	0.329	0.28	0.305	0.292	0.319
w/o IE	0.311	0.264	0.308	0.292	0.311	0.286	0.338
w/o IT	0.354	0.301	0.335	0.317	0.36	0.298	0.348
w/o LT	0.261		0.28	0.268	0.261		0.286

w/o LU	0.311	0.264	0.32	0.274	0.311	0.274	0.309
w/o LV	0.311	0.264	0.332		0.292	0.323	
w/o MT	0.378	0.322	0.415	0.268	0.354	0.286	0.281
w/o NL	0.261		0.289	0.353	0.261		0.303
w/o PL	0.292		0.308	0.305	0.298	0.286	0.338
w/o PT	0.286		0.308	0.292	0.286	0.261	0.319
w/o RO	0.261		0.28		0.274		
w/o SK	0.274		0.298	0.268	0.286	0.261	0.281
w/o SL	0.36	0.311	0.348	0.311	0.36	0.323	0.338
w/o SE	0.274		0.348	0.292	0.286	0.286	0.309
w/o UK	0.311	0.25	0.329	0.28	0.298	0.261	0.303

Note. Only significant correlations (*p< .1) are reported.

Table A2.6: Information transmission in the presence of governmental ineffectiveness and corruption, by EU Member State.

C	$F(i,j;\delta)_c$	$F(i,j;\gamma)_c$
AT	0.85	0.84
BE	0.81	0.79
BG	0.50	0.46
CY	0.80	0.71
CZ	0.70	0.56
DK	0.94	0.99
EE	0.74	0.68
FI	0.94	0.95
FR	0.79	0.79
DE	0.81	0.84
EL	0.61	0.49
HU	0.64	0.57
IE	0.78	0.83
IT	0.59	0.51
LV	0.63	0.53
LT	0.63	0.54
LU	0.84	0.91
MT	0.74	0.69
NL	0.85	0.93
PL	0.62	0.59
PT	0.71	0.71
RO	0.46	0.46
SK	0.67	0.56
SL	0.72	0.69
ES	0.69	0.71
SE	0.90	0.95
UK	0.81	0.81

Notes. $F(ij,\delta)_c$ and $F(ij,\gamma)_c$ are constructed by taking the average of the indicators on 'Government Effectiveness' and 'Control of Corruption' over 2008-2010 (Worldwide Governance Indicators, World Bank, http://info.worldbank.org/governance/wgi/index.aspx#reports), and by normalizing them to (0,1).

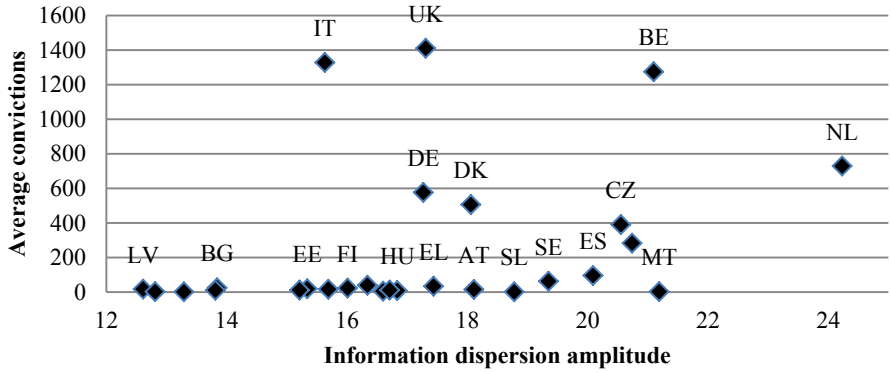

Figure A2.1: Average convictions vs. Information dispersion amplitude.

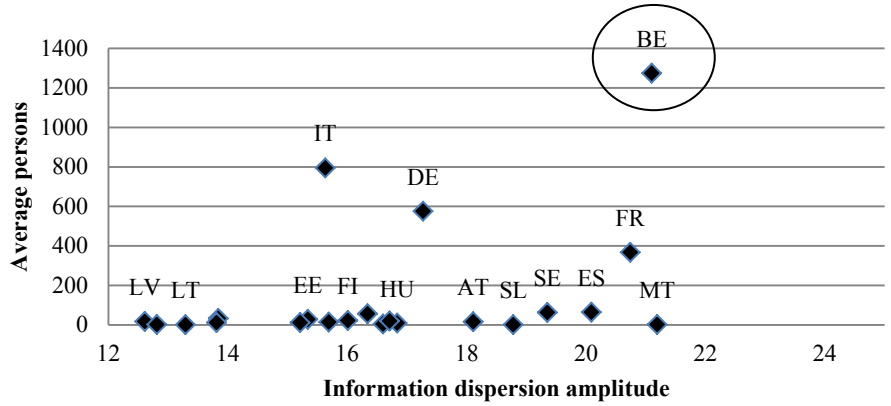

Figure A2.2: Average persons prosecuted or convicted vs. Information dispersion amplitude. The red circles mark the outliers that have also been confirmed econometrically.

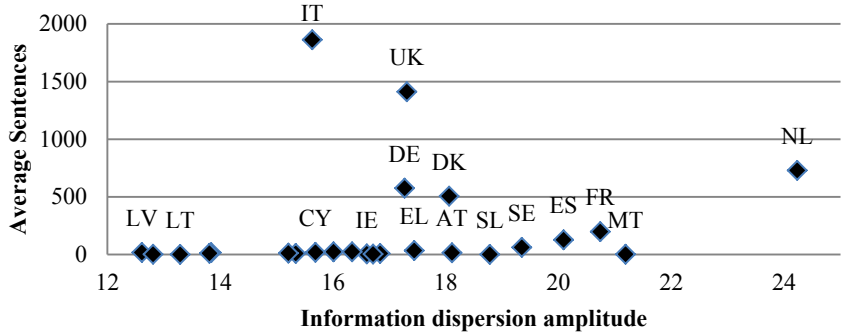

Figure A2.3: Average sentences vs. Information dispersion amplitude.

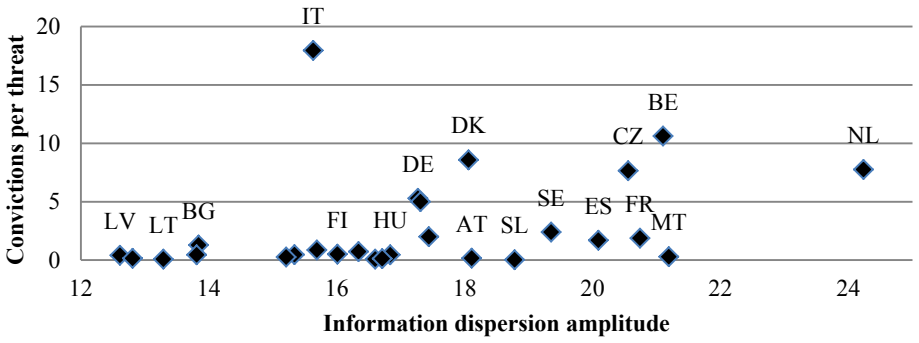

Figure A2.4: Convictions per billion of threat vs. Information dispersion amplitude.

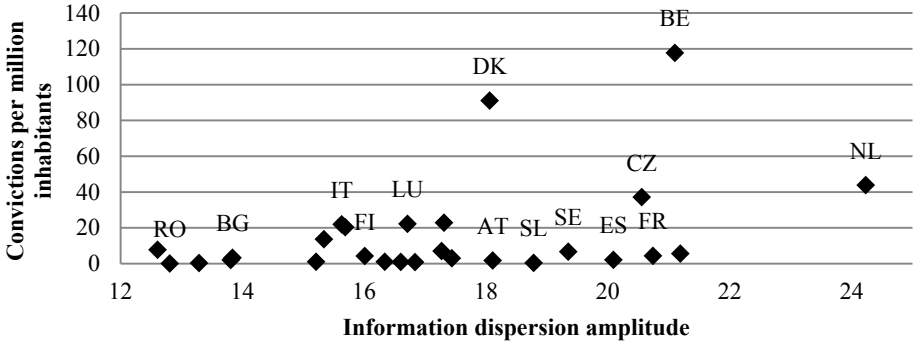

Figure A2.5: Convictions per million inhabitants vs. Information dispersion amplitude.

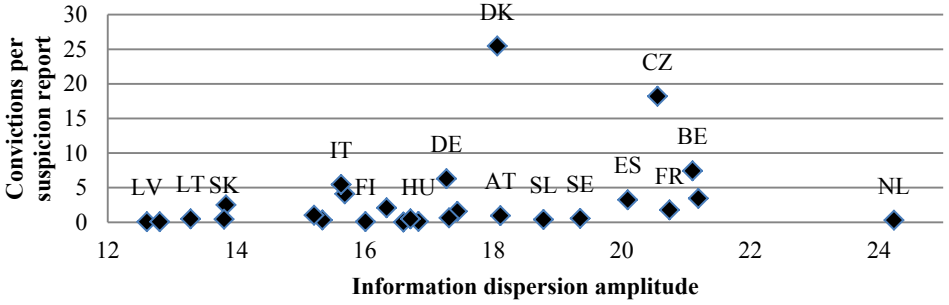

Figure A2.6: Convictions per suspicion reports vs. Information dispersion amplitude.

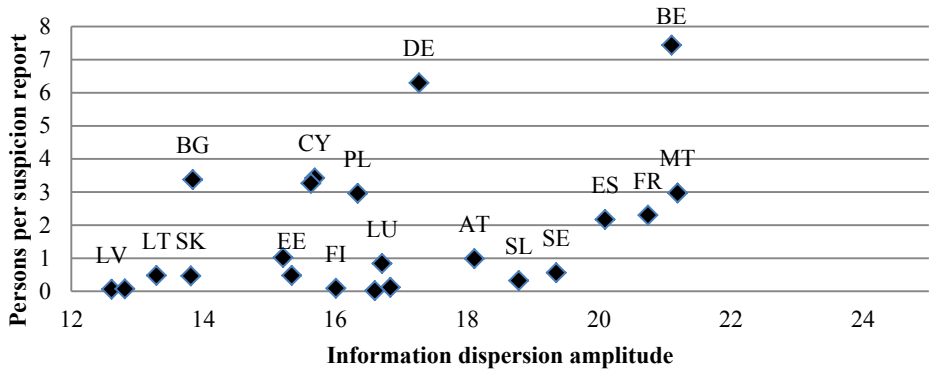

Figure A2.7: Persons prosecuted/ convicted per suspicion reports vs. Information dispersion amplitude.

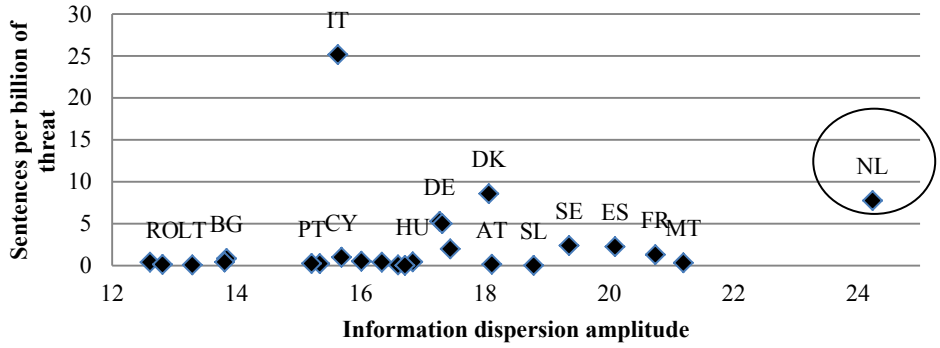

Figure A2.8: Sentences per billion of threat vs. Information dispersion amplitude. The red circles mark the outliers that have also been confirmed econometrically.

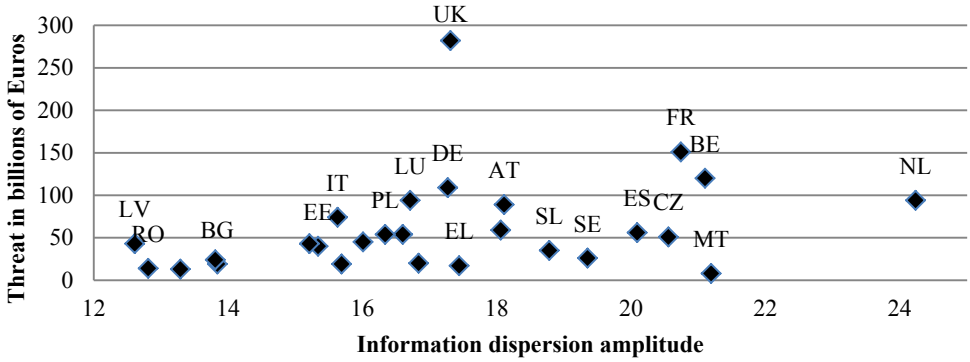

Figure A2.9: Threat (in billions of Euros) vs. Information dispersion amplitude.

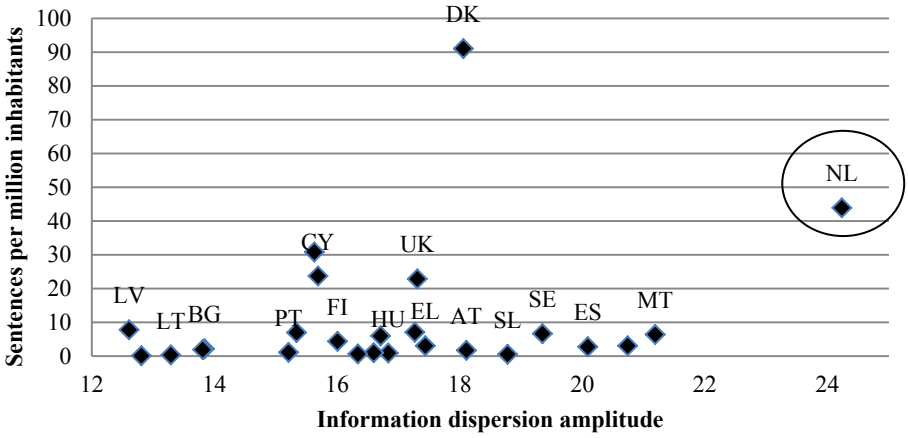

Figure A2.10: Sentences per million inhabitants vs. Information dispersion amplitude. The red circles mark the outliers that have also been confirmed econometrically.

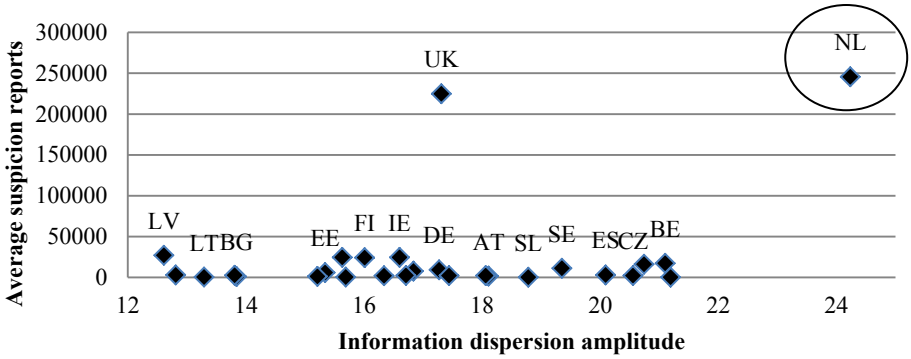

Figure A2.11: Average number of suspicion reports vs. Information dispersion amplitude. The red circles mark the outliers that have also been confirmed econometrically.

Appendix – Chapter 3

Derivation of Proposition 3

The 3rd round of Mutual Evaluations was the first round of evaluations based on the 3rd AML/CFT EU Directive and, therefore, set the reputation of a country. At this point $E[\theta_1] = E[\theta_2] = 0{,}5$, which means that the overall efforts to tamper with statistics before the MER are

$$\rho_{Before} = \sum_{i=1}^{q} \rho_i = \sum_{i=1}^{q} \frac{\beta^{\frac{1}{1-\beta}}(1+r)^{\frac{t_i}{1-\beta}}}{2^{\frac{1}{1-\beta}}} \qquad \text{(In this case we have } q = 27\text{)}$$

After the round of international evaluations, x countries received a negative evaluation and $27 - x$ a positive one. For simplicity I assume extremes, such that

$$\rho_{After} = \sum_{i=1}^{x} \rho_i + \sum_{i=x+1}^{27} \rho_i = \sum_{i=1}^{x} \frac{\beta^{\frac{1}{1-\beta}}(1+r)^{\frac{t_i}{1-\beta}}}{1{,}5^{\frac{1}{1-\beta}}} + \sum_{i=x+1}^{27} \frac{\beta^{\frac{1}{1-\beta}}(1+r)^{\frac{t_i}{1-\beta}}}{2{,}5^{\frac{1}{1-\beta}}}$$

Since $\beta < 1 \rightarrow 1 - \beta > 0$. Furthermore, $\rho_i \geq 0, \forall i$, which means that if $\rho_{Before} < \rho_{After}$ then ${\rho_{Before}}^{1-\beta} < {\rho_{After}}^{1-\beta}$. This means that I need to find the threshold x_{min} such that $\rho_{Before}^{1-\beta}(x_{min}) < \rho_{After}^{1-\beta}(x_{min})$. This translates to

$$\beta \frac{\sum_{i=1}^{27}(1+r)^{t_i}}{2} < \beta \frac{\sum_{i=1}^{x}(1+r)^{t_i}}{1{,}5} + \beta \frac{\sum_{i=x+1}^{27}(1+r)^{t_i}}{2{,}5} \tag{3.3}$$

Since after the 3rd Round of Mutual Evaluation, the next evaluation is a FUR, the time to evaluation is constant across countries, $t_i = 2$. For parsimony, I assumed it to be the same before the evaluation as well. Equation (3.3) then becomes $\frac{x(1+r)^2}{(27-x)(1+r)^2} > \frac{5}{3} \rightarrow x > 16.875 \rightarrow x_{min} = 17$.

This was a crude simplification that proved that, if sufficient countries are negatively evaluated, data deviates more after the round of mutual evaluations than before.

Data description

Table A3.1 reports on the availability of statistics on money laundering across the EU, from 2003 to 2010, excluding the null statistics, as the latter did not allow for the application of Benford's law. Although national samples are sufficiently scattered, some countries (*a.o.* Greece, Ireland, Poland and Slovakia) had too few observations to allow for the application of Benford's law while distinguishing between countries. I, therefore, pooled together country statistics to construct sufficiently large datasets (see Section 3.4).

Table A3.1: Number of available statistics on money laundering (by year) and degree of scatter, per EU Member State.

	#Obs in 2003	#Obs in 2004	#Obs in 2005	#Obs in 2006	#Obs in 2007	#Obs in 2008	#Obs in 2009	#Obs in 2010	Total # Obs	Scatter
AT	2	11	13	11	14	21	21	23	**116**	**9**
BE^{X}			3	6	7	26	25	25	**92**	**7**
BG	13	17	13	13	17	23	20	22	**138**	**8**
CY	10	10	12	11	14	20	17	22	**116**	**7**
CZ^{X}	10	10	11	11	11	15	16	17	**101**	**8**
DE	12	12	16	16	16	23	25	22	**142**	**10**
DK^{X}	7	11	7	11	12	19	18	18	**103**	**7**
EE	7	9	13	15	20	26	26	23	**139**	**8**
EL^{X}	6	6	6	6	6	16	12	11	**69**	**7**
ES	15	16	16	16	16	22	24	15	**140**	**8**
FI	14	17	18	18	20	27	26	26	**166**	**7**
FR^{X}	4	7	8	9	9	25	25	15	**102**	**9**
HU	6	8	12	13	13	25	25	24	**126**	**7**
IE^{X}	10	11	11	13	13	8	8	8	**82**	**6**
IT	8	8	10	16	17	22	24	25	**130**	**9**
LT^{X}	4	9	10	10	12	17	16	19	**97**	**8**
LU	9	12	12	16	14	19	23	22	**127**	**6**

LV	12	13	15	18	19	22	23	19	**141**	**7**
MT	14	9	12	13	17	20	22	19	**126**	**7**
NL	14	15	14	16	16	21	21	21	**138**	**8**
PL[x]	1	4	8	8	12	20	13	9	**75**	**8**
PT	7	6	9	11	13	23	22	22	**113**	**8**
RO	3	5	14	17	20	25	25	24	**133**	**8**
SE	6	8	8	11	13	22	22	22	**112**	**8**
SK[x]	1	1	3	7	13	18	19	20	**82**	**6**
SL[x]	7	8	9	10	10	19	19	19	**101**	**9**
UK	14	14	14	14	0	18	21	21	**115**	**9**
EU-27	**216**	**257**	**297**	**336**	**364**	**562**	**558**	**533**	**3122**	**9**

Notes. Dark columns sum observations across time or across countries. [x] too few observations to correctly apply Benford's law.

Recommendation 13 states that financial organizations should report any transactions or activity where they suspect money laundering to the FIU (FATF, 2003, p.5). Recommendation 32 states that countries should review their effectiveness by maintaining accurate statistics (FATF, 2003, p.9). Falling under Recommendations 13, 16 and 32, my dataset (Table A3.2) includes the number of suspicion reports forwarded by credit institutes, life insurance companies, investment firms, money transfer agencies, exchange offices, lawyers, notaries, real estate agents, traders in goods of value above Euros 15,000, casinos, external accountants or auditors and other obliged entities (Eurostat, 2010, pp.27-30; Eurostat 2013, pp.27-32). Falling under Recommendation 32 alone, I have data (Table A3.2) on the number of cases brought to prosecution originating from suspicion reports, cash transaction reports and independent law enforcement investigations; the total number of persons or legal entities convicted for money laundering offences; and the number of sentences for money laundering offences (Eurostat, 2010, pp.54-67, Eurostat, 2013, pp.63-73). Further, recommendation 27 states that designated law enforcement authorities should be made responsible for investigating money laundering, and that for this purpose they should make use of the available special investigative techniques (FATF, 2003, p. 8). Falling under Recommendations 27 and 32, I have data (Table A3.2) on the number of postponement orders adopted on reported transactions (Eurostat, 2013, pp.33-35) and on the number of money laundering investigations

carried out independently by law enforcement agencies, without a prior suspicion report (Eurostat, 2013, pp.36-38). Recommendation 31 states that policy makers, FIUs, supervisors and law enforcement should cooperate and coordinate in order to effectively combat money laundering (FATF, 2003, p.9). Falling under Recommendations 31 and 32, I have data (Table A3.2) on the number of suspicion reports sent by the FIU to the law enforcement which are thereafter investigated; and on the number of cases initiated by law enforcement agencies on the basis of suspicion reports sent by the FIU (Eurostat 2010, pp.48-53, Eurostat, 2013, pp.57-62). Finally, special recommendation IX states that countries should be able to detect the physical cross-border transportation of currency and bearer negotiable instruments and to stop those that are suspicious and to sanction those who do not truthfully report on their cash cross-border transports (FATF, 2004a, p.2). Falling under the Special Recommendation IX, I have data (Table A3.2) on the number of declarations made in application to the EU Cash Control Regulation on entering the EU and on leaving the EU; on the amounts in millions of Euros that these declarations contained; on the number of incorrect cash declarations or findings as a result of customs controls in the EU at external borders - on entering and on leaving the EU; on the amounts in millions of Euros that these incorrect declarations contained (Eurostat, 2010, pp. 31-34, Eurostat, 2013, pp. 41-43); and on the number of suspicious cash activities at the EU borders that are reported to the FIU (Eurostat 2010, pp. 35-38, Eurostat 2013, pp. 44-47).

Table A3.2: Number of observations per indicator of effective repression (by year), and degree of scatter, pooled across the EU.

	#Obs in 2003	#Obs in 2004	#Obs in 2005	#Obs in 2006	#Obs in 2007	#Obs in 2008	#Obs in 2009	#Obs in 2010	Total # Obs	Scatter
Repression statistics										
#Postponement orders [x]	8	11	14	15	17	17	19	17	**117**	**3**
#Border reports [x]	7	9	8	10	15	17	15	16	**97**	**3**
#ML investigations without SR [x]	6	9	11	14	15	14	14	15	**98**	**3**
#SR analyzed by Law Enforcement	9	12	16	18	20	19	18	18	**130**	**4**
#Law Enforcement cases from SR	13	14	15	19	20	18	12	13	**124**	**4**
#ML prosecutions	8	12	13	19	22	23	18	17	**132**	**4**
#Persons convicted [x]	9	12	15	19	20	22	20	16	**133**	**3**
#ML sentences [x]	11	13	16	19	19	16	17	14	**125**	**3**
Cross border cash movements statistics										
#Incorrect cash declarations entering the EU [x]						22	21	24	**67**	**3**
#Incorrect cash declarations on leaving the EU [x]						19	25	21	**65**	**3**
Total # of incorrect cash declarations [x]						25	25	24	**74**	**3**
Amount of cash incorrectly declared [x]						23	25	24	**72**	**4**
#Cash declarations on entering the EU [x]						27	27	27	**81**	**4**
#Cash declarations on leaving the EU [x]						26	26	26	**78**	**4**
Total # of cash declarations	6	6	6	7	18	27	27	27	**124**	**4**
Amount of cash declared at borders [x]					6	27	27	27	**87**	**5**
Suspicion reports statistics										
#SR from investment firms [x]	9	7	12	9	12	16	13	8	**86**	**3**

#SR from exchange offices [x]	9	8	8	10	10	10	9	9	**73**	**4**
#SR from notaries [x]	8	9	7	9	10	14	16	14	**87**	**2**
#SR from accountants & auditors [x]	7	7	10	11	13	16	16	13	**93**	**4**
#SR from casinos [x]	7	12	11	12	11	14	16	16	**99**	**3**
#SR from traders high value goods [x]	4	4	6	10	7	11	11	9	**62**	**3**
#SR from lawyers [x]	6	10	15	14	17	19	18	17	**116**	**3**
#SR from real estate agents [x]	3	6	9	12	12	12	13	14	**81**	**2**
#SR from life insurance companies [x]	11	13	18	17	15	16	16	19	**125**	**3**
#SR from credit organizations	20	22	24	25	24	26	26	24	**191**	**4**
#SR from money transfer companies	14	15	16	19	16	16	21	19	**136**	**5**
#SR from other obliged entities	17	20	21	22	20	24	22	20	**166**	**5**
Total no of SR	24	26	26	26	25	26	25	25	**203**	**4**

Notes. Dark columns sum observations across time. [x] too few observations to correctly apply Benford's law.

Table A3.2 shows that only a few variables have sufficient observations and are sufficiently scattered, to allow for applying Benford's law. Applying Benford's law to those variables that are not sufficiently scattered or too small, Benford's law would be rejected by the way the sample is constructed. A meaningful application of Benford's law needs a higher level of aggregation, and therefore I cannot conclude anything about variable specific variations using this dataset. For the same reason, as Table A3.1 showed, I have refrained from using Benford's law to compare deviations across EU member states. For both exercises, more data needs to be collected.

Robustness checks

Table A3.3 reports on the conformity to Benford's law given the temporal distance to the international evaluation, of three statistics: cross border cash movements, the repression and suspicion reports. First of all, data on cross border cash movements is too scarce to draw any conclusions on the fact that deviations from Benford's law decrease over time. This may be consistent with the procedural problems hypothesis introduced in section 3.2. Countries may not have had in place the mechanisms to control cash movements before the 3rd AML/CFT EU Directive, and this may have accounted for much of the deviations in the beginning of my sample. Consequently, as countries gained experience, the deviation may have therefore decreased. Conversely, strategic tampering may be harder to implement with respect to data on cross-border cash movements, as this data appears in statistics on both sides of the border. Tampering would therefore require international coordination. The reliability of this data may, thus, likely be ensured by traditional data checking mechanisms employed by Eurostat.

With respect to the statistics on the repression of money laundering, these are also scarce. I therefore looked only at the second evaluation cycle, and saw that, indeed, deviations were higher the year before the writing of the FUR than the year when the FUR was written. Finally, I had sufficient data for analyzing statistics on suspicion reports using Benford's law. These statistics deviated significantly only when furthest away from an international evaluation (Table A3.3).

Table A3.3: Robustness check: assessment of conformity to Benford's law before and during evaluations of three subsamples: cross border cash movements, repression and suspicion reports statistics.

Variables	N	χ^2	KS	$V_N{}^*$	χ^2/N	m	d^*	*Scatter*
Cash stats at MER-2 ^{X}	*23*	*6.69*	*0.125*	*1.34***	*0.29*	*0.18*	*0.26*	9
Cash stats at MER-1 ^{X}	*35*	*3.35*	*0.066*	*0.68*	*0.10*	*0.04*	*0.09*	10
Cash stats at MER ^{X}	*50*	*4.5*	*0.06*	*0.71*	*0.09*	*0.06*	*0.10*	10
Cash stats at FUR-1 ^{X}	*55*	*10.23*	*0.1*	*1.14*	*0.19*	*0.06*	*0.11*	10
Cash stats at FUR ^{X}	*81*	*8.19*	*0.126**	*1.16*	*0.10*	*0.06*	*0.10*	9
Cash stats at FUR+1	*140*	*3.64*	*0.066*	*0.84*	*0.03*	*0.05*	*0.06*	9
Repressive stats at MER-3 ^{X}	*53*	*4.02*	*0.117*	*0.99*	*0.076*	*0.13*	*0.14*	4
Repressive stats at MER-2 ^{X}	*82*	*9.62*	*0.099*	*1.44***	*0.117*	*0.07*	*0.11*	4
Repressive stats at MER-1 ^{X}	*102*	*10.85*	*0.065*	*1.26**	*0.106*	*0.06*	*0.10*	4
Repressive stats at MER ^{X}	*11*	*18.05***	*0.092*	*0.99*	*0.161*	*0.08*	*0.10*	4

	2							
Repressive stats at FUR-1	*12*	*12.62*	*0.125***	*1.41***	*0.103*	*0.13*	*0.14*	
	2		***					4
Repressive stats at FUR	*12*	*9.26*	*0.048*	*0.84*	*0.073*	*0.05*	*0.09*	
	6							4
Repressive stats at FUR+1 [x]	*11*	*15.27**	*0.069*	*1.35***	*0.132*	*0.07*	*0.11*	
	6							3
SR stats at MER-3 [x]	10	14.5*	0.097	1.30**	0.141	0.010	0.014	
	3							4
SR stats at MER-2	15	8.67	0.076	0.98	0.055	0.006	0.007	
	9							5
SR stats at MER-1	18	10.02	0.041	0.74	0.055	0.003	0.005	
	1							5
SR stats at MER	18	8.45	0.068	1.35**	0.045	0.005	0.006	
	7							5
SR stats at FUR-1	14	13.13*	0.095**	1.27*	0.088	0.008	0.010	
	9							4
SR stats at FUR	16	9.75	0.08*	1.04	0.058	0.004	0.006	
	7							5
SR stats at FUR+1	15	15.53**	0.137***	1.72***	0.102	0.006	0.009	
	3							5

Notes. [a] Stats at MER-3, ML stats at MER-2, ML stats at MER-1 and ML stats at MER aggregate statistics on money laundering that were published 3,2 and 1 year before and respectively during the year of the international evaluation. Stats at FUR-1 and ML stats at FUR aggregate the statistics published the year before and respectively during the compilation of the FUR. ML stats at FUR+1 aggregate statistics on money laundering that were published the year the FUR was published and discussed in the plenary. [X] too few observations or degrees of scatter to correctly apply Benford's law. *p< .1, **p< .05, ***p< .01.

Figure A3.1 plots data in table A3.3. Spikes in deviations occurred at the beginning of the assessment cycles and by the end of an assessment cycle, deviations were smallest. Given data availability, this is confirmed best in the subsample 'suspicion reports statistics'. Finally, the five measures followed similar patters especially when data was sufficiently scattered and samples were sufficiently large, an aspect that was, so far, too little emphasized in the empirical literature using Benford's law.

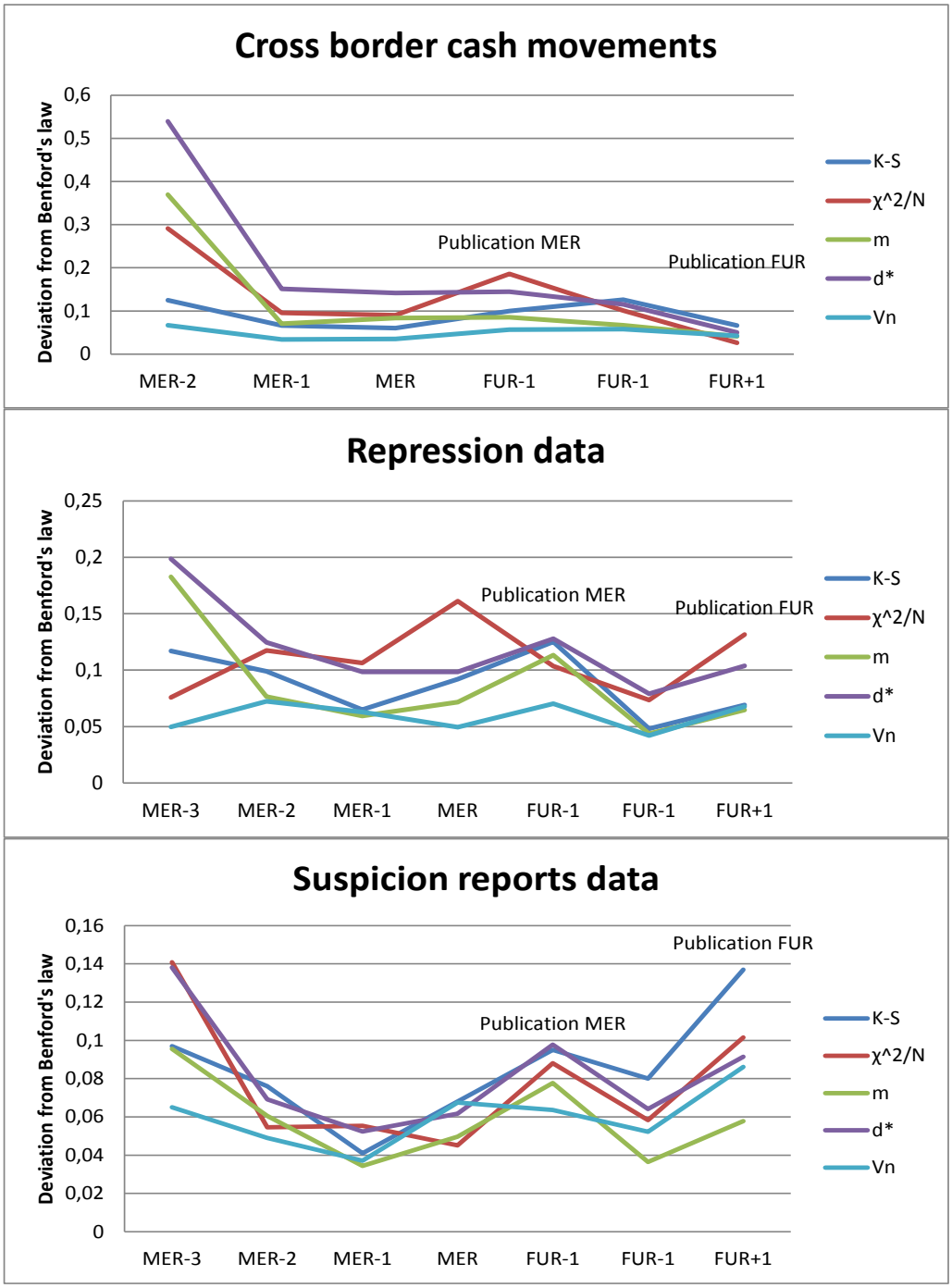

Figure A3.1: Robustness check: timely assessment of conformity to Benford's law of three subsamples: cross border cash movements, repression and suspicion reports statistics.

While in accordance with Table A3.3, for visual purposes the measures m and $d\mathrm{d}^*$ have been multiplied by a factor 10 and $V_N \mathrm{V_N}^*$ has been divided by a factor 20.

Table A3.4 reports on the application of Benford's law on two groups. The first group contained statistics of countries that were well evaluated on their efforts to monitor the cross-border cash movements (see special recommendation IX in Table 3.1), and the second group contained the statistics of countries that were not well evaluated on the same recommendation. Surprisingly, deviations were higher for the better ranted countries than for the worse rated countries. Samples were both large enough and scattered enough to ensure validity of the results.

Table A3.4: Assessment of conformity to Benford's law of statistics on cross border cash movements published after the international evaluation.

Variables	N	χ^2	KS	$V_N{}^*$	χ^2/N	m	d^*	*Scatter*
1: CY, CZ, DE, ES, IT, MT, PL, PT, SL, UK	225	9.31	0.01*	1.38*	0.04	0.03	**0.07**	**10**
2: AT, BE, BG, DK, EE, EL, FI, HU, IE, LT, LU, LV, RO, SE, SK	311	7.33	0.33	0.93	0.02	0.02	0.04	9

Note. *p< .1, **p< .05, ***p< .01.

Table A3.5 reports on the conformity to Benford's law of three subsamples before and since the MER was published: data on the effort of law enforcement/ the repression statistics, data on cash cross-border movements and data on suspicion reporting. Once again, samples were composed such that they were both sufficiently large and scattered to allow for the application of Benford's law. Table A3.5 shows that statistics on cross-border cash movements deviated less after the MER was published, confirming the conclusions drawn from table A3.3 and table A3.4. In line with Proposition 3, statistics on repression of money laundering deviated relatively little before the MER was published but strongly and significantly afterwards. Statistics on suspicion reports, on the other hand, deviated significantly both before and after the MER was published, the difference being the relatively higher deviation afterwards.

Table A3.5: Robustness check: assessment of conformity to Benford's law (before and after the publication of the MER) of three subsamples: repression, cross border cash movements and suspicion reports statistics.

Variables	N	χ^2	KS	$V_N{}^*$	χ^2/N	m	d^*	*Scatter*
Repression stats before MERp	406	8.44	0.039	1.20*	0.02	0.001	0.002	4
Repression stats since MERp	582	39.01***	0.099***	2.64***	0.07	0.004	0.005	4
Cross-border cash stats before MERp	112	10.79	0.056	1.00	0.10	0.005	0.009	10
Cross-border cash stats since MERp	536	8.55	0.042	1.23*	0.02	0.001	0.002	10
Suspicion reports stats before MERp	763	11.09	0.044**	1.42**	0.01	0.002	0.002	5
Suspicion reports stats since MERp	755	17.03**	0.069***	1.90***	0.02	0.002	0.002	5

Notes. Statistics marked 'before MERp' aggregate data from 2003 until the year before the MER was published; statistics marker 'since MERp' aggregate data from the moment the evaluation is published until 2010. *p< .1, **p< .05, ***p< .01.

Appendix – Chapter 4

Table A4.1: Description of variables and data sources.

Variable	Description	Source
wIA_TECH	weekly number of new technically relevant English articles returned to Google searches of BITCOIN	
wIA_LEG	weekly number of new legally relevant English articles returned to Google searches of BITCOIN	
wIA_FIN	Weekly number of new financially relevant English articles returned to Google searches of BITCOIN	
wP_USD	weekly price (exchange rate between a BITCOIN and the USD) in USD	*www.bitcoincharts.com*
wTV_BTC	weekly trade vol. of BITCOINs on financial markets (in BTC)	*www.bitcoincharts.com*
wBNV_BTC	weekly trade vol. of BITCOINs outside financial markets	*www.bitcoincharts.com*
wWiIKI_search	Earlier used proxy for investor attention; average weekly searches on WIKIPEDIA of the term BITCOIN	*www.wikipediatrends.com*
Google_trend	Earlier used normalized weekly proxy for investor attention; weekly average Google queries on BITCOIN	*www.google.com/trends*

Table A4.2: Functional taxonomy of the BITCOIN corpus by source of information.

Source	Source & document functional characteristics
(M) Merchant	The site offers a service/good/ alternative currency for which payments are to be made in BITCOINs. The site may be written as a blog.
(B) Blog	The site contains information posted by one or max two people; information can be technical, reflective, artistic etc; site does not have as main object of activity selling services/ goods or alternative currency.
(N) News	The site is dedicated to broadcasting news without a particular specialization on finance/ technology or politics, and when site is not a blog – *i.e.* where at least 3 individual authors are publishing, or where an editor/ team of editors is involved
(T) Tech	The site is dedicated to technological issues; addresses in particular BITCOIN miners; site is not a blog.
(F)Finance	The site is dedicated to financial/ commercial, banking, or business; site is not a blog.
(L) Legal	The site is dedicated to political or regulatory goals; site supports an organization that does politics or regulation; information originating from the site can be used to enforce behaviour; site is not a blog.
(A) Academic	The site has a scientific accreditation/ recognition; articles/ opinion pieces are published in the sphere of a (self proclaimed/ open source) research institute/ publication service.
(D) Discussion	The site is organized as a forum for discussion; information is presented as questions and answers; site is not a blog.
Not relevant	All discarded information; site is unavailable; site cannot be opened – due to virus warning or password restriction; site includes a URL with word 'bitcoin' without specifying the word in the text; site includes the word BITCOIN without relevance to the topic; site does not include the word BITCOIN; site contains only audio/visual material that cannot be text analyzed; site contains text in non-English language; information presented on the site is a summary of a broader source that the database already contains; the only reference to BITCOINs is given by a comment – thus not posted from the site owners/ administrators.

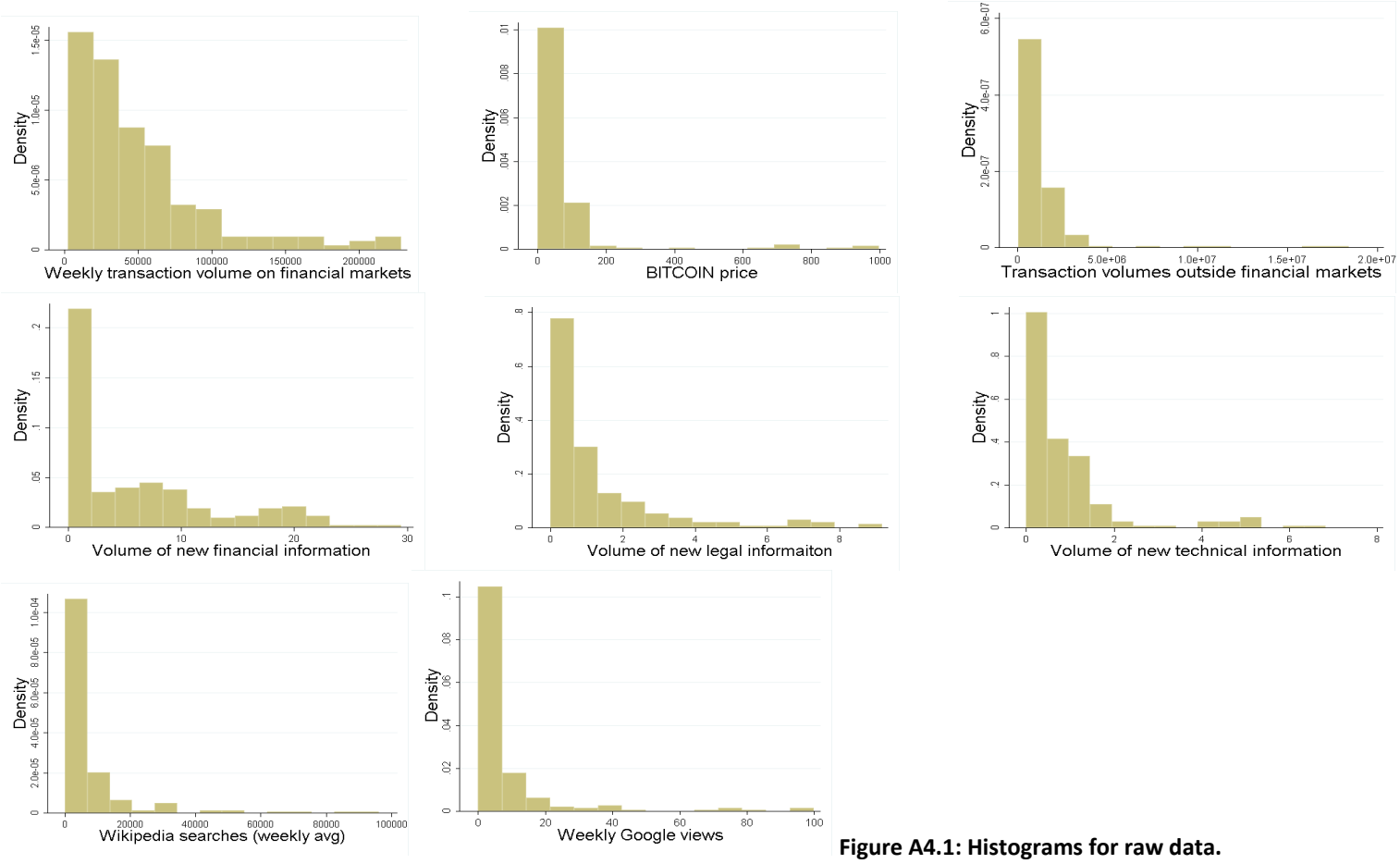

Figure A4.1: Histograms for raw data.

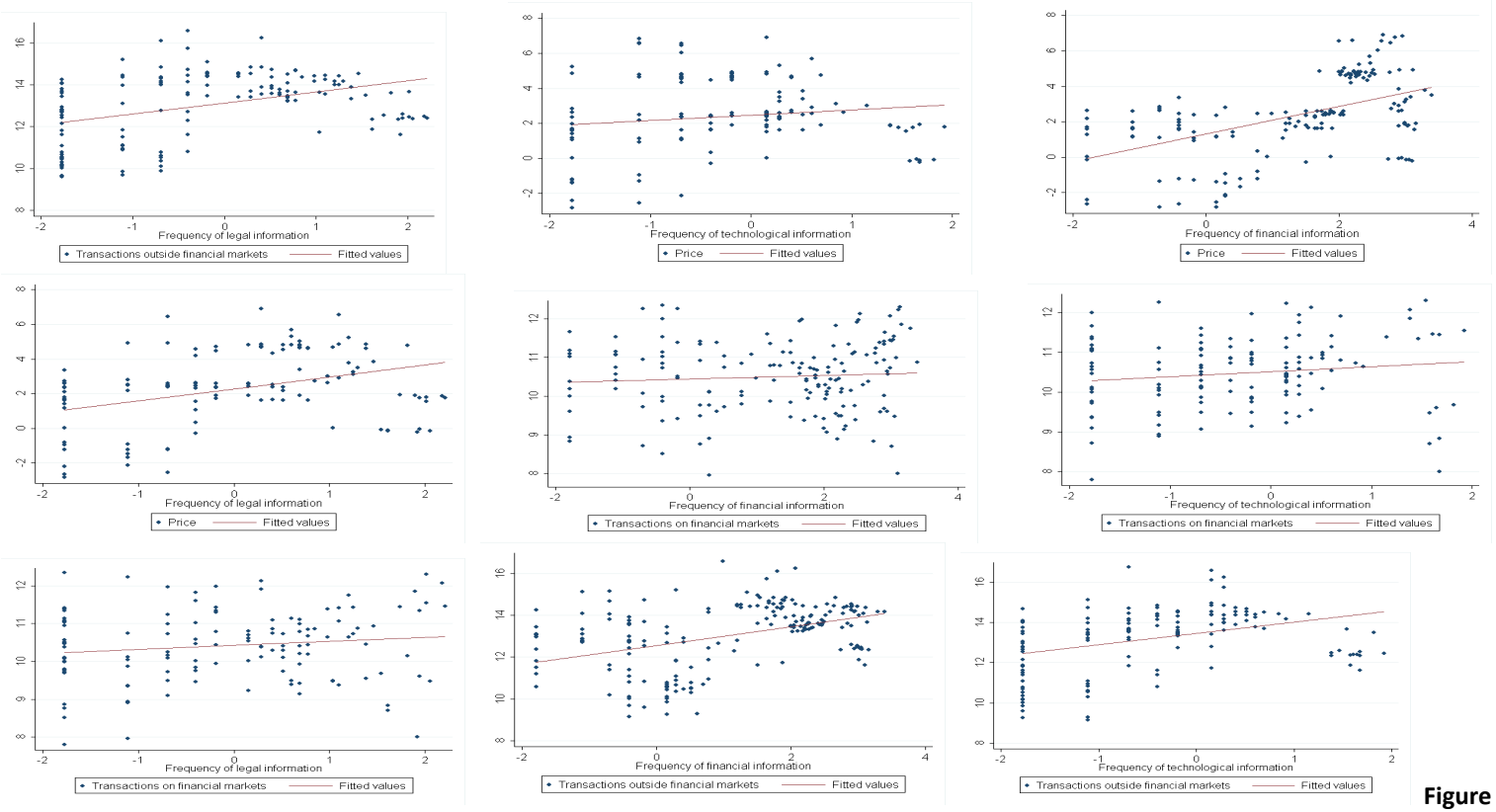

Figure A4.2: A graphical description of the correlation between BITCOIN prices, volumes of transactions and three proxies for investor arousal. The Y-axes depict price and volumes and the X-axes, the proxies for investor arousal. The fitted-value lines show the strength of each correlation.

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Summary

In this PhD thesis I address important topics in the debate on and the organisation of the Anti-Money Laundering efforts, which are related to the legitimacy and the effectiveness of the Anti-Money Laundering policies. First of all, this thesis provides a reflection on the assessments of concern that trigger policy makers in the field of crime fighting. Secondly, it provides an assessment of the effectiveness of the agencies entrusted with fighting money laundering at a national level and, of the country blacklisting practices of the Financial Action Task Force.

This thesis adheres to the literature of law and economics, while trying to approach the analysis of money laundering from a concept of choice that reflects human behaviour as real as possible. Essentially, this thesis builds on the premises that Anti-Money Laundering policies are socially embedded, that a money launderer's sentiment is socially founded and psychologically bounded and that our understanding of the effectiveness of Anti-Money Laundering efforts will benefit from an explicit consideration of these premises.

Four independent studies compose this PhD thesis. The first study looks at one of the core methods to estimate the underground economy, and argues for a behavioural change in the theoretical micro-foundations of this method. The study contends that by recognizing the psychophysical limitations of tax payers we are in a better position to measure the cash based underground economy and explain why, in some cases, the seminal measurement method of Tanzi (1983) is not applicable. Subsequently, the second study explores how the value of information is modified when transmitted hierarchically among institutions that play a role in the fight against money laundering. The study argues that by recognizing the role of institutional distance in the framing of communication between law enforcement organizations, we can enhance our capacity to measure and address the issue of effective cooperation. The third study is built on the behavioural finding that individuals perform badly at generating random numbers and maintains that international evaluations on performance may trigger strategic tampering with national statistics on money laundering. The study reflects on the effectiveness and legitimacy of the naming and shaming strategy that countries are subject to, when statistics are not objective representations of the truth. Finally, the fourth study looks at what may be the future of money laundering in the age of anonymous digital currencies. This study argued that if we recognize that individuals address uncertainty by relying on the common pool of experiential knowledge, then, the dynamics of the wisdom of the crowds may help us better anticipate future social outcomes, among which the global usage of BITCOINs for criminal purposes.

Nederlandse Samenvatting

Dit proefschrift behandelt belangrijke zaken in het debat over de organisatie van de strijd tegen witwassen, gerelateerd aan de legitimiteit en effectiviteit van het anti-witwasbeleid. Allereerst wordt in dit proefschrift gereflecteerd op de beoordelingen van beleidsmakers op het gebied van misdaadbestrijding. Daarnaast geeft het proefschrift een analyse van de effectiviteit van de instanties die belast zijn met het anti-witwasbeleid op nationaal niveau en het gebruik van zwarte lijsten door de Financial Action Task Force – de internationale organisatie die wereldwijd landen aanspoort tot anti-witwasbeleid.

Dit proefschrift sluit aan bij de juridische en economische literatuur en benadert tegelijkertijd de analyse van witwaspraktijken vanuit een keuzeconcept dat menselijke gedragingen zo goed mogelijk weerspiegelt. In essentie is dit proefschrift gebouwd op het idee dat anti-witwasbeleid sociaal is ingebed, dat de beweegredenen van een witwasser sociaal gefundeerd en psychologisch gebonden zijn en dat een expliciet begrip van deze ideeën ons helpt de effectiviteit van anti-witwasbeleid beter te begrijpen.

Dit proefschrift is opgebouwd uit vier onafhankelijke studies. De eerste studie analyseert één van de belangrijkste methodes om de omvang van de schaduweconomie te schatten en pleit voor een gedragsverandering in de theoretische micro-grondslagen van deze methode. Deze studie stelt dat we, door de psychofysische beperkingen van belastingbetalers te erkennen, beter in staat zijn om de omvang van de op contant geld gebaseerde schaduweconomie te schatten en beter kunnen uitleggen waaromde rudimentaire schattingsmethode van Tanzi (1983) niet in alle gevallen toepasbaar is.Vervolgens verkent de tweede studie hoe de waarde van informatie verandert als de informatie hiërarchisch door verschillende anti-witwasinstanties doorgegeven wordt. Deze studie stelt dat we het concept van effectieve samenwerking beter kunnen doorgronden en meten als we de rol van institutionele afstand onderkennen in de uitwerking van communicatie tussen rechtshandhavingsinstanties. De derde studie is gebaseerd op de gedragsmatige bevinding dat individuen slecht in staat zijn om willekeurige getallen te genereren en stelt dat internationale prestatie-evaluaties kunnen leiden tot strategisch geknoei met nationale witwasstatistieken. Deze studie gaat in op de effectiviteit en legitimiteit van de 'namingandshaming' strategie waar landen momenteel aan onderhevig zijn wanneer statistieken de waarheid niet goed weerspiegelen. Ten slotte kijkt de vierde studie naar de mogelijke toekomst van witwassen in een tijdperk van anonieme digitale valuta. Deze studie stelt dat als we erkennen dat individuen onzekerheid inschatten op basis van gemeenschappelijke ervaringen, de dynamiek van deze collectieve kennis ons kan helpen beter in te spelen op toekomstige maatschappelijke ontwikkelingen, waaronder het wereldwijde gebruik van BITCOINs voor criminele doeleinden.

Curriculum Vitae

Ioana Deleanu (1986) was born in Iaşi, Romania, where she completed her high-school education at The Mihai Eminescu National College in 2005. She then moved to the Netherlands to study Economics and Law at Utrecht University School of Economics (USE), and received her Bachelor degree in 2008. During her Bachelor, Ioana joined the Honours Programme of Utrecht University, which she successfully completed in 2008. From 2008 to 2010 she followed the Research Master Multidisciplinary Economics at the University of Utrecht, obtaining her Master degree in 2010. In October 2010, Ioana became a PhD candidate at USE, where she completed her dissertation in 2015. During her PhD, Ioana participated in two large scale EU funded research projects: on the effectiveness of anti-money laundering and countering terrorism financing policies in the 27 EU Member States (for DG HOME); and on evaluating the scale of corruption in public procurements (for OLAF). In June 2014 she was awarded a 'Seed money' grant from Utrecht University, a subsidy for research proposals with a high potential to receive and attract funding. This grant successfully materialized into a one year Visiting Researcher Fellowship at Yale Law School starting in December 2015. Her research interests cover the dynamics between the innovations and the trends of financial crime, and the corresponding crime fighting strategies.

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