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Money Laundering as a Crime in the Financial Sector

A New Approach to Quantitative Assessment, with an Application to Italy♣

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Abstract

Anti–money laundering regulations have been focused on the "Know-Your-Customer" rule so far, overlooking the fact that criminal proceeds that need to be laundered are usually represented by cash. This is the first study aimed at providing an answer to the question of how much cash deposited via an official financial institution can be traced back to criminal activities. The paper develops a new approach to measure money laundering and then proposes an application to Italy, where cash is still widely used in transactions and criminal activities generate significant proceeds to be laundered. In particular, we define a model of cash in-flows on current accounts and capture the presence of "dirty money" to be laundered with two indicators for the diffusion of crimes related to both illegal trafficking and extortions, considering also the structural (legal) motivations to deposit cash, as well as the need to conceal proceeds from shadow economy. Using a panel of 91 Italian provinces observed over the period 2005-2008, we find that the amount of cash laundered is sizable, around 6% of GDP (5% illegal trafficking and 1% extortions). Furthermore, the incidence of money laundering by illegal trafficking is higher in the North than in the South, while the reverse is true for extortions. These estimates are robust to several robustness checks, and – more importantly – are coherent with estimates of the non-observed economy obtained in previous studies.

JEL classification: K42, H26, G28

Keywords: Money laundering, Enterprise syndicate, Power syndicate, Shadow economy, Cash in-flows, Banking regulation

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1. Introduction

Financial sector crimes are defined – in a broad sense – as any non-violent crimes involving a (regulated) financial institution that result in financial losses because of fraud or embezzlement (e.g., IMF, 2001; FBI, 2011). Financial institutions can be involved in such crimes as victims, as perpetrators, or just as instrumentality. Check and credit card frauds are examples of crimes in which financial institutions are victims. The sales of fraudulent financial products are an example of crimes in which financial institutions are perpetrators. Money laundering is the most important example of the third type of crime. Money laundering is defined by the U.S. Department of Justice as "*the process by which criminals conceal or disguise the proceeds of their crimes or convert those proceeds into goods and services. It allows criminals to infuse their illegal money into the stream of commerce, thus corrupting financial institutions and the money supply, thereby giving criminals unwarranted economic power*" (FBI, 2011). According to estimates provided by the Financial Action Task Force (FATF) – an intergovernmental body created in 1989 by the G7 to fight money laundering and terrorism financing – criminal proceeds laundered via the international financial system could reach about 2% of global GDP (IMF, 2001), posing a serious problem to governments.

The standard approach followed by regulators to face the problem has been proposed by the FATF in its *Forty Recommendations* – which significantly overlap with the *Basel Core Principle for Banking Supervision* – and has been recognized by the *Wolfsberg Group* in a self-regulation initiative involving eleven large international banks. The cornerstone of the approach is the "Know-Your-Customer" (KYC) rule, i.e., the need for financial and banking systems to be *transparent*: every transaction within the system needs to be traced to an identifiable individual (e.g., IMF, 2001). The KYC rule is, however, subject to severe limitations. For instance, Sharman (2010) suggests the possibility to set up anonymous shell companies, which can then be used to set up anonymous bank accounts.[1] This is easier to be done in tax havens that offer corporate and banking secrecy (Hines, 2010). Most of the tax havens are indeed included on the list of non-cooperative countries and territories (NCCT) by the FATF.

[1] Findley *et al.* (2012) show that "international rules that those forming shell companies must collect proof of customers' identity are ineffective".

However, an important issue – which has been somewhat overlooked in regulation initiatives so far – is that criminal proceeds to be laundered *are usually represented by cash*. As it is well known, cash is different from other payment instruments in that it guarantees anonymity: banknotes passing from hand to hand without a trace, reducing the degree of transparency of the financial and banking systems (e.g., Payments Council, 2010). Despite this, and despite the high costs for banks to manage the cash cycle (e.g., because they need to refill ATMs networks), cash is still largely used in the world economy. In Europe, for instance, the euro cash-in circulation has doubled since euro coins and notes became legal tender in 2002, even if this measure excludes the high-denomination banknotes that are most commonly hoarded (e.g., Capgemini and Royal Bank of Scotland, 2011).

How much of the cash deposited via a regulated financial institution can be traced back to criminal activities? In this paper we try – for the first time – to provide an answer to this important question, developing a new approach to measure money laundering. Then we propose an application of this approach to Italy, a country where cash is still widely used and non-cash payment methods are not well developed, where criminal activities generate significant cash proceeds that needs to be laundered and the underground economy contributes to increased demand for cash that is then fed back into the financial system (e.g., Ardizzi *et al.*, 2014). The new methodology proposed here is based on the flows of cash pumped into the financial system, and will thus provide a *lower bound estimate* of the amount of money laundered at its very early stage. Still, this represents a significant improvement with respect to available estimates, which, instead of being based on econometric models using observed data, are almost exclusively derived from data generated by the calibration of theoretical models (e.g., Barone and Masciandaro, 2011, and Argentiero *et al.*, 2008, for Italy).

The remainder of the paper is structured as follows. In Section 2 we define a new approach to measure money laundering: we present our methodology, based on the specification of an econometric model of demand for cash deposits, and formulate testable hypotheses. In particular, we distinguish the "dirty money" component of the flows of cash deposited in current (bank and postal) accounts from the legal and the shadow economy proceeds, and then discuss the variables affecting each of these three components. In Section 3 we first discuss the estimates of the model considering alternative sources of the demand for cash deposits, and then we provide estimates of the size of money laundering at the national and the provincial levels. We also test the robustness of our findings in four directions: (1) a different specification of the econometric model, which explicitly accounts for unobserved heterogeneity across provinces; (2) the exclusion from the sample of border provinces where illegal proceeds could be laundered using foreign banks; (3) the exclusion from the cash in-flows of those referred to firms, corporations and other financial institutions, since households are likely to have a different behaviour with respect to firms; and(4) a different indicator for the presence of crime. Finally, after a brief summary, some policy implications for combating money laundering are discussed in Section 4.

2. Estimating money laundering via flows of cash deposited on current accounts

2.1. Cash deposits are observable; money laundering is not

From a theoretical point of view, money laundering is a relatively easy-to-define concept: it is a criminal offense that originates from other underlying criminal activities, that amplifies the impact of crime on both regular and irregular economies in a cumulative way. More specifically, money laundering is the process by which income stemming from crimes is "cleaned up" through the legal channel (e.g., via bank transactions). Once "cleaned up", the money can then be reinvested in legal activities. According to Schneider and Windischbauer (2008), this process can be summarized in three main stages:

a) PLACEMENT: «ill-gotten gains from punishable pre-actions are infiltrated into the financial system; at this junction there is an increased risk of being revealed»;
b) LAYERING: «criminals attempt to conceal the source of illegal income through a great deal of transactions by moving around black money. Transaction intensity and transaction speed are increased withal (multiple transfer and transaction); electronic payment systems plus diverging jurisdiction and inefficient cooperation of criminal prosecution often simplify/facilitate the layering processes as well»;
c) INTEGRATION: «infiltration of transformed and transferred capital into formal economy by means of financial investments (specific deposits, stocks) or property (direct investment in real estates and companies) is primarily completed in countries promising extraordinary short odds».

While the concept is relatively easy to define theoretically, the size and the empirical relevance of money laundering are difficult to estimate, since the illicit money pumped into the financial system cannot be observed *directly*. Exploring the scale and the impact on the financial system of illicit funds is the goal of a rather new field of research – the economics of money laundering.[2] Both Schneider and Windischbauer (2008) and Barone and Masciandaro (2011) point out that the pioneering efforts to estimate money laundering provide results that are scientifically doubtful, since they seem to exploit "tacit knowledge" and "feelings" that make them not replicable and unproven (e.g., Tanzi, 1997; Walker, 1999). Moreover, there are two important limitations in the current literature. First, the type of predicate crimes (i.e., the crimes from which proceeds are laundered) considered to assess the size of money laundering has been limited almost exclusively to narcotics trafficking (e.g., Barone and Masciandaro, 2011; UNODC, 2011), while criminal organizations actually engage in a number of other crimes. Second, and more important, most of the recent available studies consider data generated from the calibration of theoretical models instead of actual data, which often muddle up the laundering activities with the shadow economy, two linked but different phenomena (e.g., Argentiero *et al.*, 2008).

The approach proposed here improves the accuracy of current estimates and stems from the well-known Currency Demand Approach used to estimate the size of shadow economy, another phenomenon that cannot be observed directly. While money laundering is unobservable, other variables *essentially related to money laundering* are indeed observable. Among these, cash deposited via a regulated financial institution is probably the most significant observable variable. Since cash in-flows are at least partially attributable to criminal proceeds that need to be laundered, what one must do to estimate the size of money laundering is to distinguish illegal proceeds from criminal activities and from other determinants of in-flows, including legal and illegal profits from tax evasion. In other words, one needs to run a decomposition exercise, and identify the share of cash in-flows attributable to each of their determinants.

In order to identify the relevant variables for separating cash in-flows from money laundering from cash in-flows from other activities, let us consider a very simple theoretical framework, which we borrow from Masciandaro *et al.* (2007). Suppose that $U(M^l)=M^l$ is the utility

[2] Argentiero *et al.* (2008), Barone and Masciandaro (2011), Masciandaro *et al.* (2007), Schneider (2010) and Unger (2007, 2009) all provide surveys of the available literature.

function of risk-neutral criminal groups, criminals derive utility from laundered money M^l, whereas dirty money M^d does not provide any benefits (i.e., $U(M^d)=0$). We assume that criminals can launder their dirty money M^d in two alternative ways, either by depositing money in a bank account D, or by purchasing real assets R. The two options differ in the combination of risk and the return that they offer. In particular, following Masciandaro *et al.* (2007), we consider that buying real assets is more secure but less profitable; while laundering money via the financial system is more risky (because of the anti-money laundering regulations in place) but also more profitable (since the laundered money can then be used in a wide range of allocation choices). For simplicity, let the probability of detection and also the benefit from real asset purchases be zero; on the contrary, let $p \in (0, 1)$ be the probability of detection in the banking system, and $b>0$ be the expected benefits per unit of money laundered. Assuming that total benefits are linear in the amount of money laundered by deposits, while fees t to be paid once detected increase nonlinearly, the expected utility from money laundering can be written as:

$$E[U(M^l)] = (1-p)b\left(\frac{D}{M^d}\right) - pt\left(\frac{D}{M^d}\right)^2 \qquad [1]$$

Maximizing eq. [1] with respect to the share of criminal proceeds to be laundered via a bank deposit, one arrives at:

$$D^* = \frac{(1-p)b}{2pt} M^d \qquad [2]$$

Eq. [2] clarifies that money laundered via the financial system should increase with the amount of criminal proceeds M^d to be laundered and the expected benefits b, while it should decrease with the probability of detection p and the fees to be paid t.

From this theoretical framework, one can easily derive an empirical model for *observable* total cash in-flows (*INCASH*), with the purpose of disentangling the "dirty money" component D^* in the spirit of the Currency Demand Approach. Notice that, besides D^*, alternative sources of cash in-flows come from legal activities as well as from proceeds of the shadow economy. We call them $\boldsymbol{X}^{ML}$, $\boldsymbol{X}^{L}$, $\boldsymbol{X}^{SE}$, which are the determinants of cash in-flows. Considering the theoretical framework above, proxies for M^d, b, p and t should all clearly be included in $\boldsymbol{X}^{ML}$. Assuming a linear relationship between *INCASH*, $\boldsymbol{X}^{ML}$, $\boldsymbol{X}^{L}$, and $\boldsymbol{X}^{SE}$, with conditionally independent errors ($E(\varepsilon_{it} | X^{ML}{}_{it}, X^{L}{}_{it}, X^{SE}{}_{it}) = 0$), one can obtain a model like the following eq. [3]:

$$INCASH_{it} = \beta_0 + \sum_k \beta_k X^{ML}{}_{it} + \sum_h \beta_h X^{L}{}_{it} + \sum_j \beta_j X^{SE}{}_{it} + \varepsilon_{it} \qquad [3]$$

from which to estimate the size of *INCASH* due to factors $\boldsymbol{X^{ML}}$. The main issues are therefore to define *INCASH* and to identify proxies to be included in $\boldsymbol{X^{ML}}$, $\boldsymbol{X^{L}}$, and $\boldsymbol{X^{SE}}$, which are what we do next, bearing in mind that our empirical exercise will focus on Italy and particularly on Italian provinces.[3]

2.2. Observable cash deposits

We define *INCASH* as the ratio of the *value of total cash in-flows* on current (bank and postal) accounts to the *value of total non-cash in-flows* credited to current (bank and postal) accounts. This ratio basically represents the portion of non-traceable funds per euro in relation to those traceable. The cash deposits defining the numerator of *INCASH* include both cash in-flows at bank and postal branches, and via *ATM* or other automatic cash machines. The geographical distribution is related to the province of the bank or postal branch in which the customer holds the current account. The value of total incoming non-cash payments credited to bank accounts (i.e., the denominator of *INCASH*) is defined by the total value of funds credited to the current accounts by the following payment instruments: negotiated checks, transferred credits, direct debits on the payee's side, credits to the account by collection items, and incoming card payments. Also in this case, the geographical distribution refers to the province of the bank or postal branch in which the clients hold the current accounts and hence where funds are credited. In the case of incoming payments related to payment cards, the geographical distribution refers to the province in which the point-of-sale device is located.

Before moving further, notice that, considering cash in-flows on current (bank and postal) accounts, our estimation strategy will cover only step (a), the PLACEMENT, in the process of money laundering. Moreover, notice that our estimates of "dirty money" can be interpreted

[3] According to EUROSTAT, Provinces corresponds to the NUTS 3 level in the Italian territorial subdivisions. Variance is large both in terms of land area (from about 7,000 km² for Cuneo and Foggia to less than 1,000 km² for Trieste), resident population (from more than 4 millions in the province of Rome to less than 100,000 in that of Isernia), and – more importantly – per capita GDP (from 13,505 € for Sassari to 39,082 € for Milan in 2008). We account for these differences in what follows.

as a *lower bound* of the whole volume of money laundered within a country. In fact, illegal money directly converted into other assets (such as real estates, diamonds, gold and vehicles) is not considered here, since the focus of this study is the role of regulated financial institutions. Finally, we do not consider illegal cash brought to alternative remittance providers for the placement outside of the banking system (e.g., "money-transfers" agents). However, notice that since money deposited in the bank (bank money) is essential to transform capital into profitable investments in the global formal economy, it is reasonable to assume that a relevant share of illegal funds placed outside the banking system will be subsequently deposited as cash in bank accounts.

2.3. Determinants of the "dirty money" component of the demand for cash deposits

According to the theoretical framework outlined above, proxying the "dirty money" component of the cash in-flows requires identifying variables capturing: the amount of money generated by criminal activities, the (expected) benefits of laundering money via the financial system, the probability of detection, and the harshness of the anti-money laundering regulations. Since our empirical exercise involves one country, regulations are assumed to be common across the provinces. Let us then concentrate on the remaining variables. In order to capture the amount of money M^d to be laundered, one needs to define preliminarily the criminal activities that generate illegal profits to be cleaned up, and then to select the variables aimed at capturing their diffusion at the provincial level. As for the definition of criminal activities, we rely on the distinction between "enterprise syndicate" and "power syndicate", originally proposed by Block (1980), which is well established in the literature on organized crime. The former concept refers to criminal groups running illegal activities such as drug trafficking, smuggling, and prostitution, while the latter refers to organized crime structures involved in the social, economic, and military control of a specific territory. Such a distinction is crucial in Italy, where organized crimes have "headquarters" predominantly located in the South, while the "retail markets" for goods and services (such as drug and prostitution) prove to be more lucrative in the richest Central-Northern regions of the country (e.g., Ardizzi *et al.*, 2014).

The relative presence of "power syndicate" (*POWER*) at the provincial level is measured by the number of *detected* crimes[4] from extortions within the province (normalized by its sample mean value). The choice to focus on extortions is motivated by the fact that this is the prevalent tactic through which criminal organizations gain control of territory at the local level. For instance, Gambetta (1993) points out that the Sicilian *Mafia* uses extortion as «an industry which produces, promotes, and sells private protection», and Alexeev *et al.* (2004) argue that the payments extorted by criminal organizations can be viewed as additional "taxation" imposed to firms. The request for protection is made regardless of the citizens' will, and using Gambetta's words «whether one wants or not, one gets it and is required to pay for it». The same argument applies to the other Italian regions traditionally dominated by powerful criminal organizations, such as the *Camorra* in Campania, the *'Ndrangheta* in Calabria, and the *Sacra Corona Unita* in Puglia.[5]

The relative diffusion of "enterprise syndicate" (*ENTERPRISE*) in a province is measured by the number of detected crimes connected to drug dealing, prostitution[6], and receiving stolen properties within the province (normalized by its sample mean value). Such a proxy is able to account for those illegal services provided on the basis of a mutual agreement, as well as those imposed by violence. Indeed, drugs and prostitution-related offenses, in line with the OECD (2002) definition of illegal economy, imply an exchange between a seller and a buyer based on a mutual agreement. On the other hand, receiving stolen property is defined as the use of violence made to persons or properties, and then imply "payments" which do not follow an "agreement" between the thief and the victim. We believe that accounting for both types of offenses is important in our model since both activities generate proceeds to be cleaned up.

Both the variables *ENTERPRISE* and *POWER* are weighted by a GDP concentration index.[7] Such a standardization allows us to better compare provinces characterized by remarkable differences in the level of socio-economic development and, perhaps, in terms of

[4] Throughout the paper, by the number of *detected* crimes we mean the number of extortions reported to the authorities and resulted in judicial prosecutions, not the number of convictions. We are also aware that underreporting is a serious problem in Italy. Later in the paper we will introduce an alternative proxy for measuring the diffusion of extortions (*POWER*2), which allows us to account for potential underreporting.

[5] A recent and detailed study on extortion activities in the EU member states is provided in Transcrime (2008).

[6] Notice that – differently from other countries – prostitution is not prohibited *per se* in Italy, but there are a number of crimes connected with it (like, e.g., aiding and abetting prostitution, or exploiting prostitution). These are the crimes we are considering here.

[7] The GDP concentration index is defined as the ratio of provincial GDP to its sample mean value.

crime detection and contrasting, thus avoiding automatically assuming higher levels of crime (and money laundering) for provinces with the number of detected offenses above the sample mean. Recalling eq. [2] above, both indicators for the diffusion of criminal activities are expected to show positive correlations with cash in-flows. Thus, we put forward our first and main testable hypothesis:

H1: *The higher the diffusion of crime, the larger is money laundering, hence the higher the demand for cash deposits, ceteris paribus.*

In light of the above discussion about the greater diffusion of *POWER* in the (relatively poorer) Southern regions, we expect to find a higher incidence of this component of money laundering in the South. On the other hand, given the ability of criminal organizations to "export" illegal traffics from the richest areas of the country, where the demand for "goods and services" such as drugs and prostitution is presumably higher, we expect to find a larger size of money laundering from *ENTERPRISE* in the Central and the North. We then formulate this additional hypothesis:

H2: *The occurrence of money laundering component due to ENTERPRISE is relatively higher in the Central and the Northern regions, while the component due to POWER is relatively higher in the South.*

A second variable that we need to take into account to identify money laundering is the probability of detection *p*. Here we rely on a specific disposition of the Italian anti-money laundering law, which requires financial intermediaries to report to the *Unità di Informazione Finanziaria* (the Financial Intelligence Unit at the Bank of Italy) all transactions for which they know (or they suspect) that are in place (or have been in place) to launder criminal money or to finance terrorist groups. We consider in particular the number of *Segnalazioni Operazioni Sospette* (i.e., reports on irregular financial transactions) normalized by the number of current accounts (*DETECT*). From eq. [2] above, we formulate the following testable hypothesis:

H3: *The higher the probability of detection of irregular financial transactions, the less is money laundered via financial intermediaries, hence the lower the demand for cash deposits, ceteris paribus.*

Finally, one needs to account for the benefits *b* obtainable from the cash laundered via the financial system. These are defined by Masciandaro *et al.* (2007) as the returns expected from reinvestment (licit or illicit) of the money laundered. If one considers investment opportunities at the national or even international levels (e.g., a sovereign bond), then returns are even across provinces. On the contrary, if one considers *local* investment opportunities, then one can take the interest rate on deposits (*INT*), which is differentiated across provinces, as a proxy for the returns. Recalling eq. [2] above again, we formulate the following testable hypothesis:

H4: *The higher the interest rate, the higher is money laundering via financial intermediaries, hence the higher the demand for cash deposits, ceteris paribus.*

2.4. Alternative sources of cash in-flows: legal transactions and the proceeds from the shadow economy

In order to account for the determinants of *INCASH* other than money laundering, our model includes a set of variables aimed to capture the legal motivations of cash deposit demand, as well as its component linked to proceeds from the underground economy, i.e., proceeds from legal activities which are however hidden to Tax Authority in order to evade taxes. As for the legal motivations, we introduce the following controls: the degree of local socio-economic development; the diffusion of electronic payment instruments in commercial transactions; and the interest rates on bank deposits. As suggested by several studies on shadow economy (e.g., Schneider and Enste, 2000; Schneider, 2011), per capita GDP has a negative expected impact on the use of cash: the higher the average living standard, the lower is the use of cash for payments, thus the lower should be the demand for cash deposits because the volume of currency circulating at the local level is lower. The average income is highly correlated to education level (both general education and "financial literacy"), and more education usually leads to a lower use of cash, since more educated individuals show greater confidence in alternative payment instruments (World Bank, 2005). Our first measurement of socio-economic development is per capita provincial GDP (*YPC*) and the related hypothesis to be tested is as follow:

H5: *The higher the average per capita income of a province, the lower is the demand for cash deposits for legal motivations, ceteris paribus.*

We also consider the rate of unemployment at the provincial level (*URATE*) as a second possible indicator for the level of economic development. In particular, to some extent this variable reflects differences in income distribution (see, e.g., Brandolini *et al.*, 2004), thus in education levels, and is expected to exert a positive impact on the use of cash for payments, which in turn has a positive impact on the demand for cash deposits: for a given average value of per capita GDP, a higher unemployment rate corresponds to an income distribution more concentrated in high-income classes, with a larger share of low-income (and poorly educated) people relying on the use of cash for their payments. From this we formulate the following hypothesis:

H6: *The higher the unemployment rate in a province, the higher is the demand for cash deposits for legal purposes, ceteris paribus.*

A further control is needed in order to capture the cross-province variability of the average attitude towards the use of cash in transactions as an alternative to electronic payment methods. Several studies (e.g., Drehmann and Goodhart, 2000; Goodhart and Krueger, 2001; Schneider, 2009) emphasize the importance of payment technology, with particular reference to the availability of electronic instruments. Based on this literature, we account for available payment technology at the provincial level by including the variable *ELECTRO* among the legal determinants of *INCASH*. This variable measures the ratio of the value of transactions by electronic payments to the total number of current accounts. A higher share of electronic transactions implies a lower general attitude of individuals towards the use of cash and, as a consequence, a lower demand for cash deposits. Thus, the *ELECTRO* coefficient is expected to be negative:

H7: *The higher the diffusion of electronic payments in commercial transactions, the lower is the demand for cash deposits for legal purposes, ceteris paribus.*

Finally, we consider the interest rate on current deposits (*INT*) also as a possible determinant of the legal component of *INCASH*. In terms of the benefits of laundering cash, based on standard economic theory, the interest rate on deposits is expected to have a positive effect on *INCASH*, via its role of opportunity cost of holding non-interest bearing accounts. As usual, for "speculative" purpose, the *INT* coefficient is expected to be positive. However, there are at least four reasons why this is not the case. First, *INCASH* is defined by a share, which implies that a higher interest rate could impact proportionally both on its denominator and numerator, leading to a neutral overall effect. Second, our model deals with cash in-flows rather than stock of deposits, which implies an ambiguous effect of the interest rate[8]. Furthermore, the years covered by our estimations have been characterized by very low interest rates, which are likely to have strongly mitigated the speculative purpose (ECB, 2008). Finally, we notice that most recent developments in innovative banking (i.e., internet banking), which increased the products characterized by lower operational costs and higher interest rates with respect to traditional banking, might even bring about a negative relationship between *INT* and cash deposits. Given these considerations, for legal purposes, the *INT* coefficient is expected to be undetermined a priori:

H8: *The higher the interest rate on deposits, the higher/lower is the demand for cash deposits for legal motivations, ceteris paribus.*

The indicators used for controlling cash in-flows linked to proceeds from the underground economy at the provincial level are the relative weights of some economic sectors of local economies, and the diffusion of tax frauds in sales by retailers. The composition of local production by economic sectors has been found to significantly affect the size of the shadow economy (e.g., Johnson *et al.*, 2000). In particular, the shares of employment in agriculture (*EMP_AGR*) and the construction industry (*EMP_CON*) are variables traditionally used as proxies for the evasion of income tax and social security contributions, with these being the typical sectors with higher presence of undocumented workers (e.g., Torgler and Schneider, 2009; Capasso and Jappelli, 2012). As for Italy, according to the recent estimates provided by the National Institute of Statistics (Istat, 2010a), undocumented workers constituted 12.2% of total employment in 2009, and the phenomenon was particularly concentrated in the agricultural sector (24.5% undocumented workers) and the construction sector (10.5%).[9] Thus, we formulate the following hypothesis:

[8] For a more detailed discussion on recent trends of both flow and stock monetary aggregates in Italy, see Ardizzi *et al.* (2014).

[9] Although Istat provides official figures on undocumented workers in Italy, disaggregated estimates are publicly available only for the regions but not at the provincial level. The same is true for the statistics on self-employed workers, which is used by a strand of literature on shadow economy as a proxy for the employment in the informal sector (e.g., Loayza and Rigolini, 2011; Fiess *et al.*, 2010). This is the reason why we have decided to rely on the figures related to the agricultural and construction sectors in order to capture the variability in the diffusion of undocumented workers across the provinces.

H9: *The larger the employment in the agricultural and the construction sectors, the higher is the number of undocumented workers and the demand for cash deposits due to proceeds from the underground economy, ceteris paribus.*

Finally, we include in our model a variable controlling for irregularities detected by the *Guardia di Finanza* (the Italian Tax Police) through tax inspections at retailers. *COMM_FRAUDS* is given by the ratio of the number of positive audits on cash registers and tax receipts to the number of existing POS in the province. The standardization for the number of POS is made necessary by the high variability in the presence of POS across provinces, which is likely to affect the opportunity to evade tax (expected to be lower where the number of POS is higher, see Ardizzi *et al.*, 2014). This ratio is weighted by a GDP concentration index for the same reason discussed above for crime variables. Our working hypothesis is then:

H10: *The higher the diffusion of commercial tax frauds, the higher is the demand for cash deposits due to shadow economic proceeds, ceteris paribus.*

It is important to notice here that *COMM_FRAUDS* is a measure of detected tax evasion. In our model we do not include proxies for the tax burden level, like the average income tax rate, as it is usually done in CDA-based empirical models. As discussed in Ardizzi *et al.* (2014), such a choice is convenient for three main reasons. First, many factors – beyond the tax burden – are likely to influence the decision to escape Tax Authorities (market regulation, tax morale of citizens, efficiency of public administration, etc.), and each of these factors would need a proper proxy. Second, tax rates might be subject to a *reverse causality* problem. That is, for a given amount of public spending, in a country with a higher tax evasion, statutory tax rates need to be set at a higher level to keep the budget balanced. Third, to explore variations within the country, one needs specific tax rates for each sub-area, which can be difficult to obtain in the presence of even a minimal degree of tax decentralization and a number of layers of government. For instance, this is the case of Italy, where there are no data on the actual tax rate at the provincial level, and the calculation of some proxies for "fiscal pressure" is not a trivial task, since taxes are levied by different levels of government (including municipalities, provinces, and regions) on very different tax bases.

2.5. Assessing the size of money laundering

Eq. [4] below provides the complete model of the demand for cash deposits to be estimated, distinguishing the determinants of money laundering, those of the legal cash in-flows and those generated by the proceeds from the shadow economy:[10]

$$\begin{aligned} INCASH_{it} = {} & \beta_0 + \beta_1 ENTERPRISE_{it} + \beta_2 POWER_{it} + \beta_3 DETECT_{it} + \\ & + \beta_4 YPC_{it} + \beta_5 URATE_{it} + \beta_6 ELECTRO_{it} + \beta_7 INT_{it} + \\ & + \beta_8 EMP\_AGR_{it} + \beta_9 EMP\_CON_{it} + \beta_{10} COMM\_FRAUDS_{it} + \varepsilon_{it} \end{aligned} \qquad [4]$$

The size of money laundering can be assessed following two different routes. On the one hand, as is traditional in the Currency Demand Approach and in its reinterpretation proposed by Ardizzi *et al.* (2014),[11] we can estimate the "excess demand" for cash deposits unexplained by structural factors and business activities carried out in the shadow economy as the difference between the fitted values of *INCASH* from the full model [4] and the predicted values obtained from a restricted version of eq. [4], where the coefficients of *ENTERPRISE, POWER, DETECT* (and *INT*) are set equal to zero. On the other hand, one can directly use the coefficients for the determinants of money laundering to estimate the "excess demand". Both routes are equivalent, leading to the same estimates.

Given our definition of *INCASH*, money-laundering estimates obtained with these procedures are expressed in relation to total deposits generated by instruments other than cash. Thus, in order to have measurements comparable with those obtained in previous studies, we need to adjust our results and express them in terms of provincial GDP.

3. Econometric analysis

3.1. Data and estimation technique

The model of the demand for cash deposits described by eq. [4] is estimated using a panel of 91 Italian provinces observed over the period 2005-2008. The units included in the final dataset represent about 90% of all the 103 Italian provinces, and are those for which

[10] Notice that the coefficient β_7 picks up both the role of *INT* as a benefit for money laundering, as well as the role of *INT* as a determinant of the legal demand for cash deposits. We will further discuss this issue below.

[11] Notice that, as remarked by Ardizzi *et al.* (2014), this reinterpretation of the CDA originally suggested by Tanzi (1980, 1983) reduces the methodology to a decomposition exercise according to, e.g., Wagstaff *et al.* (2003), hence avoiding problems of causality in the relationships among our dependent variable and the demand factors included in model [4]. In this perspective, all our testable hypotheses should not be read as causal effects but as simple correlations between *INCASH* and each regressor.

complete information were available for all the relevant variables. The Appendix reports the definition and descriptive statistics (for the whole sample, as well as for the three macro-areas, North, Central, and South, separately) and information about the different data sources (see Tables A1 and A2).

As for the estimation technique, given the panel structure of our data and the marked heterogeneity across units (as highlighted also by the prevalence of the *between* component of standard deviation for all the variables except *INT*, see Table A2), we preliminarily check for the presence of heteroskedasticity, contemporaneous cross-sectional correlation, and autocorrelation in the residuals. Ignoring heterogeneity and possible correlation of regression disturbances over time and between units can lead to biased statistical inference (e.g., Cameron and Trivedi, 2005). However, while most recent studies provide heteroskedastic- and autocorrelation consistent standard errors, cross-sectional or "spatial" dependence in the residuals is still often ignored, thus imposing an artificial and potentially biasing constraint on empirical models. Indeed, relying on proper statistical tests, we find that all the three problems are present in the error structure of our data.[12] Therefore, in order to adjust the standard errors appropriately, we consider a Prais-Winsten regression with Panel-Corrected Standard Errors (*PCSE*). In particular, we specify that there is first-order autocorrelation within groups and that the coefficient of the AR(1) process is specific to each group.[13]

[12] Specifically, we used the Wooldridge (2002) test for autocorrelation in panel data, the Greene (2000) test for groupwise heteroskedasticity, and the Pesaran (2004) test for cross-sectional dependence in panel data. All the results ara available on request from the authors.

[13] More technical details on this estimator are discussed in Hoechle (2007) and in the original contributions by Prais and Winsten (1954) – as for the problem of serially correlated residuals – and by Beck and Katz (1995) – as for the problem of heteroskedastic and contemporaneous cross-sectionally correlated residuals.

Table 1: Estimates of cash deposit demand [4]: 91 Italian provinces, 2005-2008 (*Prais-Winsten regression with Panel-Corrected Standard Errors*)

Regressors [a]	Model 1	Model 2	Model 3	Model 4
Money laundering component [b]				
ENTERPRISE	0.0324***	0.0282***	0.0276***	0.0271***
[H1]	(3.31)	(2.61)	(2.59)	(2.70)
POWER	0.0108**	0.0133***	0.0078*	0.0072*
[H1]	(2.41)	(2.75)	(1.75)	(1.70)
DETECT	0.0039	0.0095	0.0084	-
[H3]	(0.33)	(0.62)	(0.58)	-
Structural (legal) component [b]				
YPC	-0.0068***	-	-0.0043***	-0.0051***
[H5]	(-5.00)	-	(-3.05)	(-3.98)
URATE	-	0.6574***	0.3872***	0.3661***
[H6]	-	(6.67)	(2.58)	(2.56)
ELECTRO	-0.0012***	-0.0022***	-0.0015***	-0.0014***
[H7]	(-3.65)	(-9.30)	(-6.06)	(-5.27)
INT	-0.0002	-0.0119***	-0.0037	-
[H4/H8]	(-0.05)	(-3.16)	(-0.87)	-
Shadow economy component [b]				
EMP_AGR	0.5904***	0.6128***	0.5221***	0.4907***
[H9]	(9.32)	(7.72)	(5.19)	(4.65)
EMP_CON	0.3749***	0.4510***	0.3388**	0.3683***
[H9]	(3.51)	(3.09)	(2.34)	(2.83)
COMM_FRAUDS	0.0478***	0.0758***	0.0607***	0.0565***
[H10]	(3.40)	(8.38)	(5.44)	(5.17)
Constant	0.2111***	0.0051	0.1381***	0.1583***
	(4.70)	(0.44)	(2.62)	(3.13)
Observations	364	364	364	364
Wald statistic (χ^2)	1953.92***	3541.36***	5789.94***	3429.54***
R^2	0.94	0.92	0.92	0.92

[a] Dependent variable: *INCASH* = value of total cash in-payments on current accounts normalized to the value of total non-cash payments credited to current accounts; z-statistics in parentheses.
[b] Theoretical hypothesis to which each regressor refers is indicated in squared brackets.
***, **, *: Statistically significant at 1%, 5%, 10%, respectively.

3.2. Estimates of the demand for cash deposits

Table 1 reports parameter estimates of eq. [4] according to four different specifications. In the first three models, we include only *YPC* (Model 1), only *URATE* (Model 2), or both *YPC* and *URATE* (Model 3) as control variables for the demand of cash deposits linked to the degree of socio-economic development. All these three models perform quite well in terms of fit: the Wald statistic is always significant at the 1% level, and the R^2 is above 0.90. Moreover, almost all coefficients are statistically significant and with signs consistent with our theoretical hypotheses. There are only two exceptions: one is the coefficient of the interest rate on bank deposits (*INT*), which is either insignificant (when *YPC* is included in the model), or turns negative and significant (when *YPC* is excluded), a result suggesting that *INT* is likely to play the same role as per capita income and does not capture neither the benefits of money laundered via financial intermediaries, nor the legal determinants of the demand for cash deposits.[14] The second exception is the coefficient of *DETECT*, our proxy for the probability of detection. The number of *Segnalazioni Operazioni Sospette* (i.e., reports on irregular financial transactions) is very small (37 reports per 1,000 accounts on average), implying that the current anti-money laundering regulations in Italy are likely to be ineffective.[15] In order to define the most parsimonious specification (Model 4), we then run a Wald test on the joint significance of the two coefficients for *DETECT* and *INT*: we largely fail to reject the null hypothesis $\alpha_3 = \alpha_7 = 0$ ($\chi^2 = 0.78$, p-value 0.6764).

Estimates in Model 4 (our baseline specification) confirm that the demand for cash deposits can be decomposed into three types of drivers:

(1) A *money laundering* component: both the diffusion of illegal traffics (*ENTERPRISE*) and that of extortion activities (*POWER*) prove to be positively associated with the relative size of cash in-flows [H1];

[14] Notice also that the result for *INT* was somewhat expected in light of our previous discussion in section 2.4 and the testable hypothesis H8.

[15] We also estimated an alternative model interacting our proxy *DETECT* with year dummies to capture the potential different impact of the anti-money laundering regulations across the years. However, none of these interactions turned out to be significant. Results are not included here but are available upon request from the authors.

(2) A *structural (legal)* component: the average per capita income (*YPC*) and the diffusion of electronic payments (*ELECTRO*) are negatively correlated with cash in-flows [H5-H7], while the unemployment rate (*URATE*) shows a positive correlation [H6];

(3) A *shadow economy* component: both proxies for the diffusion of undocumented workers (*EMP_AGR* and *EMP_CON*) and for the variable monitoring the presence of commercial tax frauds (*COMM_FRAUDS*) are positively associated with cash in-flows [H9-H10].

It is worth noticing that both indicators characterizing the local economy (*YPC* and *URATE*) remain highly significant when used jointly (Model 3 and Model 4). This supports our argument that the unemployment rate captures an additional (distributional) dimension of socio-economic development with respect to the average per capita income, which helps to verify the legal purposes of the demand for cash deposits.[16]

An interesting finding is highlighted by Table A3 in the Appendix, which reports the average simulated contribution of each variable to the observed demand for cash deposits (expressed in percentage of GDP and normalized to 100), by referring to our baseline specification (Model 4). The largest (negative) contribution is offered by the level of per capita GDP, while all the other regressors account for a much smaller share of the demand for cash deposits. The predicted contributions also point to sensible differences across macro-areas. In particular, the incidence of *YPC* decreases (in absolute value) from 203 in the North to only 39 in the South, becoming relatively closer to the share of *URATE* (19), which is unsurprising given the greater relevance of unemployment in southern regions. Furthermore, in accordance with our hypothesis H2, the *ENTERPRISE* component of criminal activities shows a much higher incidence in the North and in the Central than in the South (28 and 23 vs. 12), while the reverse is observed for the share of *POWER*, although with a less marked difference (5 vs. 6).

[16] On the joint use of the two variables, see also Buehn and Schneider (2012).

Table 2: Size of money laundering and total irregular economy as percentage of GDP (mean 2005-2008) – *PCSE* estimates

Model 1	**91 provinces [a]**				**82 provinces [b]**			
	ITALY	North	Central	South	ITALY	North	Central	South
ML-ENTERPRISE	6.1%	7.6%	5.6%	4.0%	4.4%	4.8%	4.5%	3.8%
ML-POWER	2.0%	1.8%	1.5%	2.6%	1.7%	1.3%	1.4%	2.5%
TOTAL ML [c]	**8.1%**	**9.4%**	**7.1%**	**6.7%**	**6.1%**	**6.1%**	**5.9%**	**6.3%**
SHADOW	14.1%	16.7%	11.1%	12.1%	12.4%	13.6%	10.5%	12.2%
TOTAL IRREG [d]	**22.2%**	**26.1%**	**18.2%**	**18.8%**	**18.6%**	**19.7%**	**16.4%**	**18.5%**
Model 2	**91 provinces [a]**				**82 provinces [b]**			
	ITALY	North	Central	South	ITALY	North	Central	South
ML-ENTERPRISE	5.3%	6.6%	4.9%	3.5%	3.9%	4.2%	3.9%	3.3%
ML-POWER	2.4%	2.2%	1.8%	3.2%	2.1%	1.6%	1.7%	3.1%
TOTAL ML [c]	**7.7%**	**8.8%**	**6.7%**	**6.7%**	**5.9%**	**5.8%**	**5.6%**	**6.4%**
SHADOW	16.7%	19.8%	13.1%	14.4%	14.8%	16.1%	12.5%	14.5%
TOTAL IRREG [d]	**24.5%**	**28.6%**	**19.8%**	**21.2%**	**20.7%**	**21.9%**	**18.1%**	**20.8%**
Model 3	**91 provinces [a]**				**82 provinces [b]**			
	ITALY	North	Central	South	ITALY	North	Central	South
ML-ENTERPRISE	5.2%	6.4%	4.8%	3.4%	3.8%	4.1%	3.9%	3.2%
ML-POWER	1.4%	1.3%	1.1%	1.9%	1.2%	1.0%	1.0%	1.8%
TOTAL ML [c]	**6.6%**	**7.7%**	**5.8%**	**5.3%**	**5.0%**	**5.1%**	**4.8%**	**5.0%**
SHADOW	13.3%	15.7%	10.3%	11.6%	11.7%	12.8%	9.8%	11.6%
TOTAL IRREG [d]	**19.9%**	**23.4%**	**16.2%**	**16.9%**	**16.7%**	**17.8%**	**14.7%**	**16.7%**
Model 4	**91 provinces [a]**				**82 provinces [b]**			
	ITALY	North	Central	South	ITALY	North	Central	South
ML-ENTERPRISE	5.1%	6.3%	4.7%	3.4%	3.7%	4.0%	3.8%	3.2%
ML-POWER	1.3%	1.2%	1.0%	1.7%	1.1%	0.9%	0.9%	1.6%
TOTAL ML [c]	**6.4%**	**7.5%**	**5.6%**	**5.1%**	**4.8%**	**4.9%**	**4.7%**	**4.8%**
SHADOW	13.4%	15.9%	10.6%	11.5%	11.8%	12.9%	10.0%	11.5%
TOTAL IRREG [d]	**19.8%**	**23.4%**	**16.2%**	**16.6%**	**16.6%**	**17.8%**	**14.7%**	**16.3%**
Observations	364	176	80	108	328	148	76	104

[a] Average values computed using the whole set of money laundering and total irregular economy estimates related to the balanced panel of 91 Italian provinces.

[b] Before computing average values, we discarded all the provinces showing an outlier estimate of *ML-ENTERPRISE*, and/or *ML-POWER*, and/or *SHADOW* in at least one year of the observed period. The 9 outliers were identified using the Hadi (1992, 1994) method and mostly correspond to the provinces with the biggest towns in Central-North.

[c] *TOTAL ML* is computed as the sum of *ML-ENTERPRISE* and *ML-POWER*.

[d] *TOTAL IRREG* is computed as the sum of *TOTAL ML* and *SHADOW*.

3.3. The size of money laundering

We assess the size of money laundering for each province in each year by considering our baseline specification, as well as the estimates in Model 1 to Model 3 as a first robustness check. For each model we compute separate measurements for the two components of money laundering (*ML-ENTERPRISE* and *ML-POWER*)[17], then we sum these up to get an estimate of the total money laundering activity (*TOTAL ML*). In order to have comparable measurements with more traditional studies on tax evasion and underground production, we also compute the size of the component of cash deposit demand linked to proceeds from the shadow economy (*SHADOW*).[18] We then sum it up with *TOTAL ML* to provide an estimate of cash in-flows from what we call the "irregular economy" (*TOTAL IRREG*), an aggregate including proceeds from the "black" and the "grey" economy.

Estimates are shown in Table 2. For each model, the table shows averages for Italy and for the three sub-samples of provinces located in the North, in the Central and in the South. These averages have been computed both by considering the complete set of 91 provinces, and by excluding 9 outlier provinces identified by the Hadi (1992, 1994) method with respect to the three components, *ML-ENTERPRISE*, *ML-POWER* and *SHADOW* jointly considered. Notice that outliers mostly correspond to the provinces with the biggest (and the richest) towns in the Centre-North – Milan, Turin, Genoa, Bologna, and Rome – and are mainly driven by the *ML-ENTERPRISE* component, thus confirming the polarization of illegal trafficking in the areas of the country where the "retail markets" for goods and services such as drugs, prostitution and receiving stolen properties are more lucrative (Ardizzi *et al.*, 2014).

Several interesting results emerge from Table 2. Firstly, considering averages computed on the complete set of provinces, the estimated size of total money laundering ranges from 6.6-6.4% of GDP in Models 3 and 4 to around 8% when using the restricted specifications of eq.

[17] As discussed before, this computation can be done in two different ways, which arrive at the same results. The traditional route is to impose the restriction that either the coefficients of *ENTERPRISE* or *POWER* are zero, and calculate the "excess demand" for cash deposits due to criminal activities linked to illegal traffics and extortions, respectively, as a difference with respect to the full model. In running this exercise, notice that we consider only statistically significant coefficients. Moreover, in Model 2, given its negative value that mirrors the role of *YPC*, *INT* has been considered among the determinants of the legal component of cash in-flows.

[18] In this case, the restriction we impose is that coefficients of *EMP_AGR*, *EMP_CON*, and *COMM_FRAUD* are jointly zero.

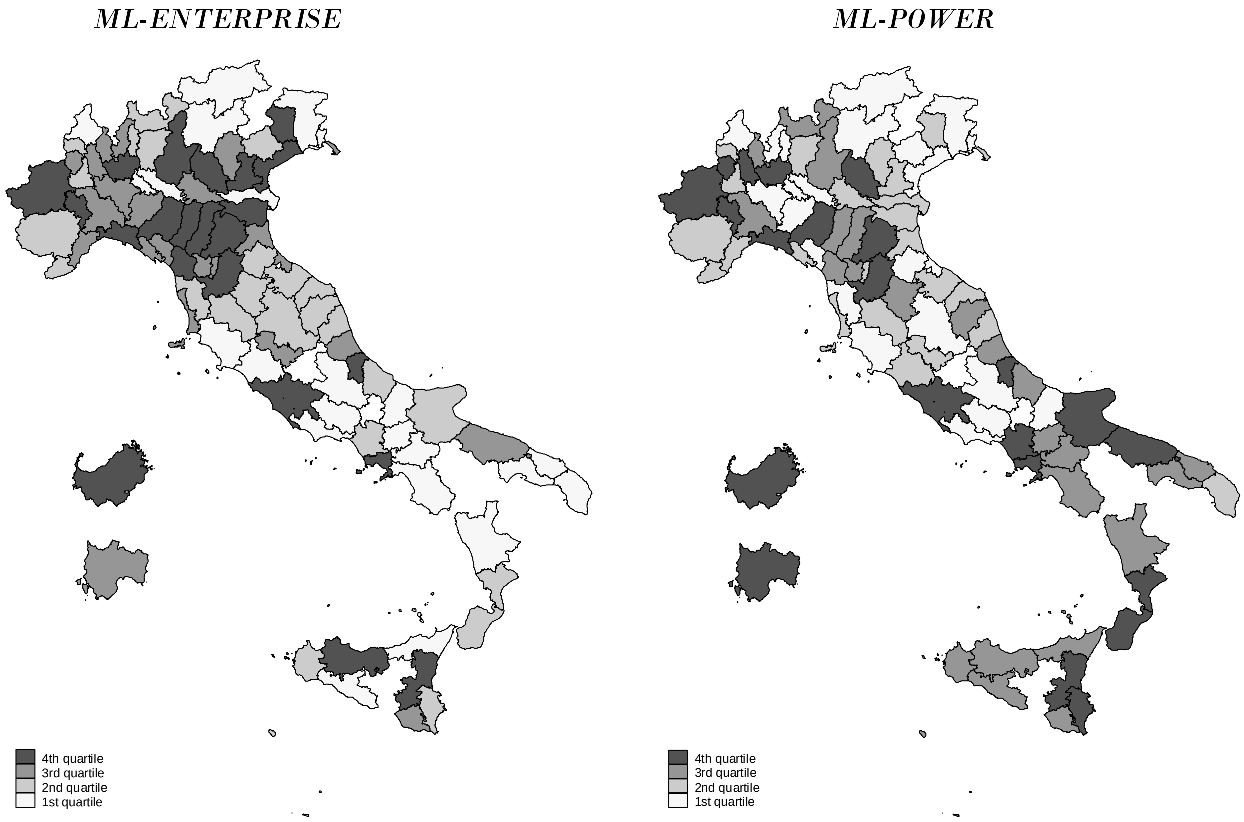
[4] that include only one indicator for the degree of socio-economic development (*YPC* in Model 1 and *URATE* in Model 2). This evidence points out that not accounting for the different features of the local economies (like the average per capita income and its distribution), one could mistakenly attribute a part of cash in-flows linked to other purposes to money laundering.

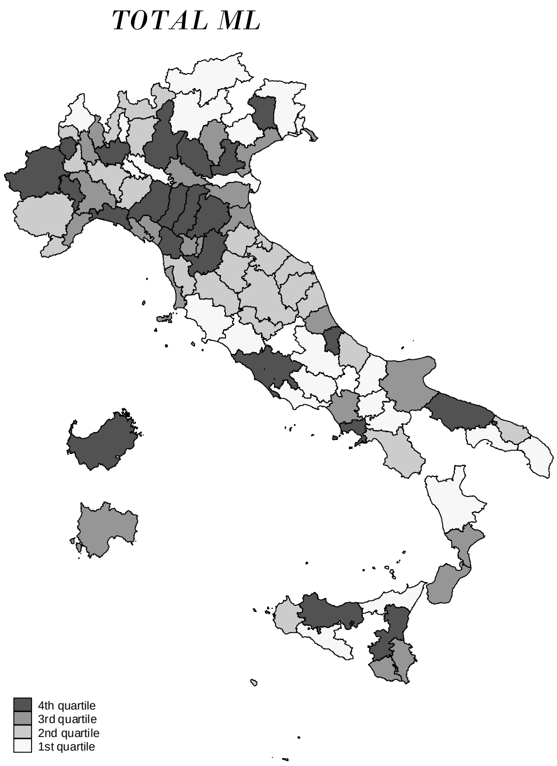
Secondly, in all models the national level estimates demonstrate that *ML-ENTERPRISE* plays a major role in determining the relative size of money laundering. In particular, according to our baseline specification (Model 4), almost 80% of total dirty money is attributable to illegal trafficking (5.1% of GDP), while about 20% is due to *ML-POWER* (1.3% of GDP). However, looking at the disaggregated estimates at the macro-area level, there are remarkable differences between Northern and Southern provinces in terms of both the entire size of money laundering and the relative contributions of the two types of criminal activities. More precisely, the share of dirty money on GDP is 7.5% in the North against 5.1% in the South. As for the incidence of *ML-ENTERPRISE* and *ML-POWER*, the former is almost two times higher in the Northern provinces than in the Southern ones (6.3% vs. 3.4%), while the opposite is true for money laundering derived from extortion activities, for which the share in the South is around 1.5 times the value of the North (1.7% vs. 1.2%). These findings support our hypothesis H2, which suggests a higher incidence of illegal trafficking proceeds in the richest areas of the country and a higher incidence of proceeds from the direct control of the territory through military power in the regions traditionally dominated by the big criminal organizations (*Mafia*, *Camorra*, *'Ndrangheta*, and *Sacra Corona Unita*). This picture emerges also from Figure 1, which shows the geographical distribution of the size of money laundering by province, distinguishing between the two components *ML-ENTERPRISE* and *ML-POWER* and the aggregate *TOTAL ML*.

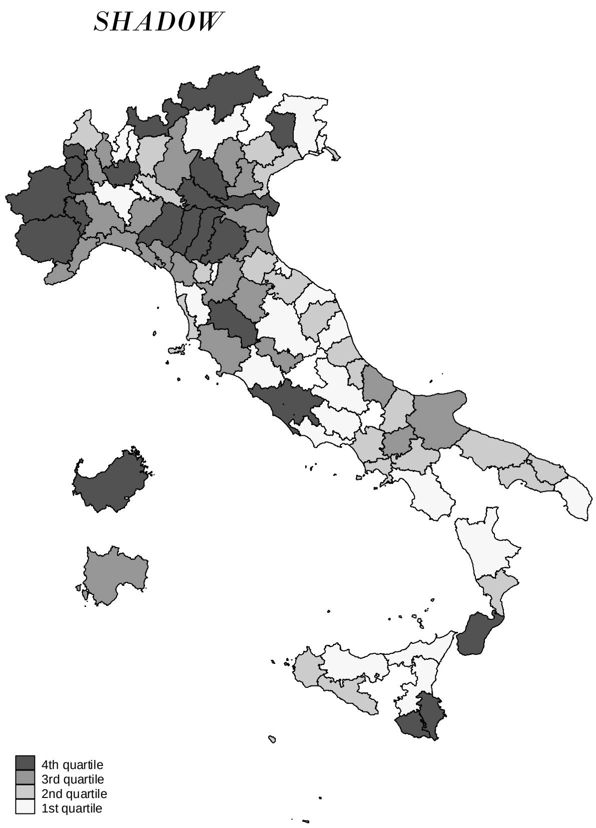
Thirdly, the size of the shadow economy ranges from 13.3-13.4% of GDP (considering the more complete Models 3 and 4) to 16.7% (using Model 2), a result that slightly underestimates the most recent results for Italy computed with a reinterpretation of the Currency Demand Approach (16.5-17.5% of GDP; Ardizzi *et al.*, 2014). This underestimation is unsurprising; given that available estimates are based on cash *out-flows* (i.e., withdrawals) from bank and postal accounts, while here we are considering cash *in-flows* on current accounts. This likely suggests that a part of the proceeds generated by legal activities but hidden to Tax Authorities are not reinvested via these accounts. Moreover, it is important to notice that our estimates here are consistent with the results of Ardizzi *et al.* (2014) in terms of the importance of *SHADOW* in the different areas of the country. In particular, results in Table 2 and Figure 1 confirm that the shadow economy is larger in Northern provinces comparing to Southern ones.

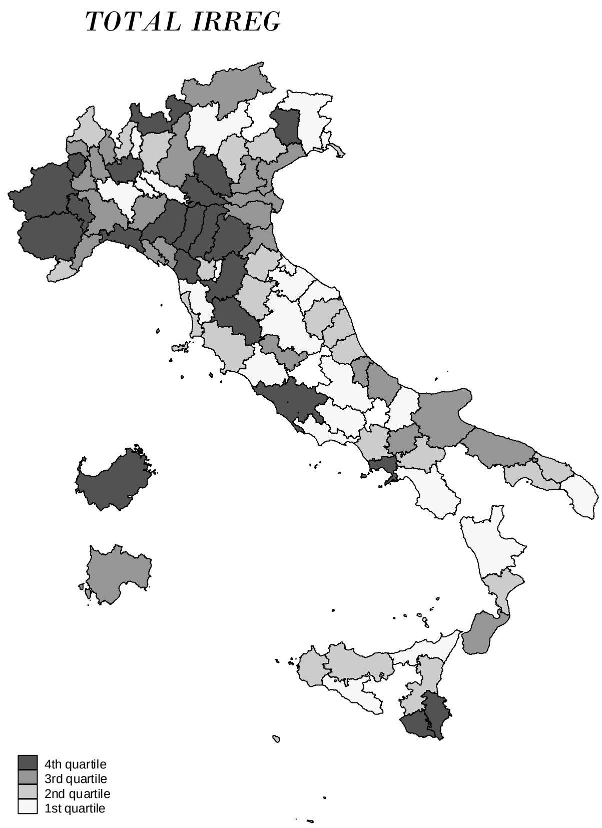
Finally, summing up money laundering and shadow economy, we obtain an estimate of the total irregular economy (*TOTAL_IRREG*) ranging from 19.8-19.9% of GDP (Model 3-4) to 24.5% of GDP (Model 2), a result that again largely agrees with available figures on the size of non-observed sector in Italy (e.g., Buehn and Schneider, 2012; Ardizzi *et al.*, 2014), which confirms the reliability of our estimates. Also for the total irregular economy we observe a marked North-South gradient: taking our baseline specification (Model 4), *TOTAL_IRREG* is estimated to be 23.4% of GDP in Northern provinces and only 16.6% of GDP in Southern ones, a result clearly driven by the relative weights of *ML-ENTERPRISE* and *SHADOW* with respect to *ML-POWER*, which is higher in the North.

Figure 1: Geographical distribution of money laundering and total irregular economy as percentage of GDP by province (*PCSE* estimates on 91 Italian provinces, mean 2005-2008 – Model 4)




TOTAL ML
4th quartile
3rd quartile
2nd quartile
1st quartile


SHADOW
4th quartile
3rd quartile
2nd quartile
1st quartile


TOTAL IRREG
4th quartile
3rd quartile
2nd quartile
1st quartile

However, as seen in Figure 1, these national and macro-area averages mask significant differences among the provinces within each of the three macro-areas, including the provinces where the money laundering is almost absent (white zones) and those where the phenomenon makes up a very large share of the local economy (dark gray zones). This is particularly obvious for the distribution of *ML-ENTERPRISE* in the Central-North, where it clearly emerges the polarization of money laundering in some provinces with the biggest towns (such as Milan, Turin, Genoa, Bologna, and Rome) that are likely to boost the most lucrative retail markets for illegal traffics. This helps explain why considering the averages computed on the restricted sample of 82 provinces (after eliminating the outliers for *ML-ENTERPRISE*, *ML-POWER* and *SHADOW* shares jointly considered), the overall size of money laundering decreases significantly (from 6.4% to 4.8% in Model 4) and also the gap between macro-areas tends to disappear, mainly as a consequence of the lowered incidence of *ML-ENTERPRISE* in the North (which reduces to 4%). Furthermore, the size of the shadow economy shrinks when dropping the outliers, as does the difference between Northern and Southern provinces in terms of *SHADOW*. However, it is worth noticing that, besides Turin and Milan, the provinces with more significant shadow economy do not overlap with those where money laundering plays a major role. Most of the former have medium-sized cities in the North (like Asti and Parma).

3.4. Robustness analyses

3.4.1. Testing the econometric model

As a first robustness check for the findings discussed above, we re-estimate eq. [4] using a Tobit Random Effects specification (*Tobit RE*), in order to explicitly account for unobserved residual heterogeneity across provinces. Comparing to a standard panel regression with random effects, this model has the advantage to accommodate for the particular distribution of our dependent variable, which is censored at zero and can assume only positive values.[19] In particular, we specify the error structure as $\mathring{\boldsymbol{U}}_{it} = u_i + e_{it}$, where u and e are individual effects and the standard disturbance term, respectively.

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[19] See, e.g., Wooldridge (2002). Notice that the theoretical distribution of *INCASH* is between 0, if all in-flows on current accounts originate from payment means other than cash, and ∞, if all in-flows are made by cash.

Table 3: Estimates of cash deposit demand [4]: 91 Italian provinces, 2005-2008 (*Tobit regression with Random Effects*)

Regressors [a]	**Model 4**
Money laundering component [b]	
ENTERPRISE	0.0297**
[H1]	(2.36)
POWER	0.0104**
[H1]	(2.21)
Structural (legal) component [b]	
YPC	-0.0058***
[H5]	(-7.41)
URATE	0.2759***
[H6]	(2.89)
ELECTRO	-0.0012***
[H7]	(-3.58)
Shadow economy component [b]	
EMP_AGR	0.4050***
[H9]	(4.49)
EMP_CON	0.2651**
[H9]	(2.36)
COMM_FRAUDS	0.0303**
[H10]	(2.31)
Constant	0.1959***
	(6.57)
Observations	364
Wald statistic (χ^2)	365.65***
σ_u	0.0379***
σ_e	0.0189***

[a] Dependent variable: *INCASH* = value of total cash in-payments on current accounts normalized to the value of total non-cash payments credited to current accounts; z-statistics in round brackets.
[b] Theoretical hypothesis to which each regressor refers is indicated in squared brackets.
***, **, *: Statistically significant at 1%, 5%, 10%, respectively.

Table 4: Size of money laundering and total irregular economy as percentage of GDP (mean 2005-2008) – *Tobit RE* estimates

Model 4	91 provinces [a]				82 provinces [b]			
	ITALY	North	Central	South	ITALY	North	Central	South
ML-ENTERPRISE	5.6%	6.9%	5.1%	3.7%	4.1%	4.4%	4.1%	3.5%
ML-POWER	1.9%	1.7%	1.4%	2.6%	1.6%	1.3%	1.3%	2.4%
TOTAL ML [c]	**7.5%**	**8.7%**	**6.5%**	**6.2%**	**5.7%**	**5.7%**	**5.5%**	**5.9%**
SHADOW	9.8%	11.6%	7.7%	8.3%	8.6%	9.4%	7.3%	8.4%
TOTAL IRREG [d]	**17.2%**	**20.2%**	**14.3%**	**14.6%**	**14.3%**	**15.1%**	**12.8%**	**14.2%**
Observations	364	176	80	108	328	148	76	104

[a] Average values computed using the whole set of money laundering and total irregular economy estimates related to the balanced panel of 91 Italian provinces.

[b] Before computing average values, we discarded all the provinces showing an outlier estimate of *ML-ENTERPRISE*, and/or *ML-POWER*, and/or *SHADOW* in at least one year of the observed period. The 9 outliers were identified using the Hadi (1992, 1994) method and mostly correspond to the provinces of the biggest towns in Central-North Italy.

[c] *TOTAL ML* is computed as the sum of *ML-ENTERPRISE* and *ML-POWER*.

[d] *TOTAL IRREG* is computed as the sum of *TOTAL ML* and *SHADOW*.

Coefficient estimates from Model 4[20] are reported in Table 3, while Table 4 shows the size of money laundering and that of the total irregular economy estimated from the same model. The results are consistent with those discussed in the previous section, both for the model coefficients and the derived estimates of the size of money laundering. More precisely, the average total size of money laundering is 7.5% of GDP if computed using the whole set of 91 provinces, and reduces to 5.7% for the restricted sample of 82 provinces, which excludes outliers of *ML-ENTERPRISE*, *ML-POWER* and *SHADOW*. Again we find a major role played by the *ML-ENTERPRISE* component and a noticeable gap between macro-areas, particularly between the North and the South: provinces in the North show a higher value of *TOTAL ML* (8.7% vs. 6.2%) due to the much greater incidence of *ML-ENTERPRISE* on the total cash laundered (6.9% vs. 3.7%), while those in the South exhibit a relatively higher share for *ML-POWER* (2.6% vs. 1.7%). Previous results are also confirmed for the shadow economy and the total irregular economy.

[20] Also in this case the estimation of Model 3, which includes *DETECT* and *INT* among the determinants of *INCASH*, resulted in statistically non-significant coefficients for these variables. A Wald test on the joint restriction fails to reject the null hypothesis.

3.4.2. Investigating the role of border provinces

As a second robustness test, we verify whether money-laundering estimates are sensitive to the exclusion of some provinces close to the borders from the sample, where illegal proceeds – instead of being invested into the Italian banking system – could be illegally exported and deposited in foreign banks. In terms of previous eq. [2], the reason for laundering money abroad is likely to relate to looser regulations with respect to the Italian ones, hence a lower probability of detection p. Capital export can clearly bias our dependent variable *INCASH*, hence our estimates of money laundering. To identify the provinces that could be more affected by the problem, we consider an investigation on the demand of high-denomination banknotes (often used to export large amounts of cash) conducted by the Bank of Italy's Financial Intelligence Unit. The ranking of the Italian provinces according to the withdrawal of € 500 banknotes per thousand inhabitants in 2009 is hardly surprising. Top listed are some small provinces located near the borders of foreign markets, particularly attractive in the perspective of exporting cash and hiding illegal proceeds due to bank secrecy, such as Como and Lecco, bordering Switzerland, and Forlì-Cesena and Rimini, bordering the Republic of San Marino.[21]

Table 5 shows the Prais-Winsten regression with *PCSE* estimates of the demand for cash deposit (Model 4) using reduced samples that excludes the provinces of Como and Lecco (restricted sample 1), the provinces of Forlì-Cesena and Rimini (restricted sample 2), and both groups of border provinces (restricted sample 3). The general goodness of fit of the model is again confirmed: the Wald statistic is always significant at the 1% level, and the R^2 is above 0.90. In all the three regressions, coefficients are largely similar to those reported in Table 1, both in terms of statistical significance and magnitude, confirming the robustness of the proposed methodology to sample perturbations accounting for potential limitations in the correct measurement of the amount of cash in-flows deposited on local current accounts. More importantly, also the estimates of the size of money laundered and the total irregular economy are confirmed. Table 6 demonstrates that compared to the evidence obtained with the full sample of 91 provinces (Table 2, Model 4), results are slightly higher excluding

[21] These data are quoted in an article published by one of the most widely read Italian newspapers, the *Corriere della Sera*, on July 24th, 2011 (Gerevini M. and Stringa G., Rischio riciclaggio, l'Italia "taglia" le maxi banconote), and are taken from a reserved report by the Bank of Italy's Financial Intelligence Unit. Unfortunately, the report is not available to us, and we cannot use these data in our exercise.

provinces bordering Switzerland (6.8%), and slightly lower excluding provinces bordering the Republic of San Marino (5.2%), and both groups (5.7%). Interestingly, in all the three exercises, the observed variation seems to be entirely attributable to *ML-ENTERPRISE*, which confirms the stronger role of illegal trafficking with respect to extortions, explainable by the greater demand for high-denomination banknotes in these four Northern provinces.

Table 5: Estimates of cash deposit demand [4]: Exclusion of border provinces with a stronger demand for high-denomination banknotes (*Prais-Winsten regression with PCSE*, Model 4)

Regressors [a]	Restricted sample 1 [b]	Restricted sample 2 [b]	Restricted sample 3 [b]
Money laundering component [c]			
ENTERPRISE	0.0289***	0.0206*	0.0230*
[H1]	(3.07)	(1.7)	(1.83)
POWER	0.0074*	0.0070*	0.0072*
[H1]	(1.73)	(1.68)	(1.70)
Structural (legal) component [c]			
YPC	-0.0050***	-0.0052***	-0.0051***
[H5]	(-3.85)	(-4.01)	(-3.85)
URATE	0.3674***	0.3861***	0.3879***
[H6]	(2.53)	(2.69)	(2.67)
ELECTRO	-0.0015***	-0.0013***	-0.0013***
[H7]	(-5.82)	(-4.72)	(-5.17)
Shadow economy component [c]			
EMP_AGR	0.5014***	0.4862***	0.4983***
[H9]	(4.44)	(4.68)	(4.51)
EMP_CON	0.3582***	0.3575***	0.3503***
[H9]	(2.70)	(2.76)	(2.7)
COMM_FRAUDS	0.0568***	0.0561***	0.0568***
[H10]	(4.94)	(5.16)	(5.07)
Constant	0.1546***	0.1656***	0.1606***
	(2.96)	(3.21)	(3.04)
Observations	356	356	348
Wald statistic (χ^2)	3613.21***	3672.42***	3620.29***
R^2	0.92	0.91	0.91

[a] Dependent variable: *INCASH* = value of total cash in-payments on current accounts normalized to the value of total non-cash payments credited to current accounts; z-statistics in parentheses.
[b] Restricted sample 1 excludes the two provinces of Como and Lecco bordering Switzerland. Restricted sample 2 excludes the two provinces of Forlì-Cesena and Rimini bordering the Republic of San Marino. Restricted sample 3 excludes both groups of border provinces.
[c] Theoretical hypothesis to which each regressor refers is indicated in squared brackets.
***, **, *: Statistically significant at 1%, 5%, 10%, respectively.

As for the differences in the direction of the bias between the provinces close to Switzerland and those bordering the Republic of San Marino, a likely interpretation is the degree of integration with the Italian payments system, which is substantially higher for banks in the Republic of San Marino with respect to that of the Swiss banks.[22]

Table 6: Size of money laundering and total irregular economy as percentage of GDP (mean 2005-2008) – *PCSE* estimates relative to restricted samples excluding border provinces with a stronger demand for high-denomination banknotes

Model 4	Restricted sample 1 [a]				Restricted sample 2 [b]				Restricted sample 3 [c]			
	ITALY	North	Central	South	ITALY	North	Central	South	ITALY	North	Central	South
ML-ENTERPRISE	5.5%	6.9%	5.0%	3.6%	3.9%	4.9%	3.5%	2.6%	4.4%	5.6%	4.0%	2.9%
ML-POWER	1.4%	1.3%	1.0%	1.8%	1.3%	1.2%	1.0%	1.7%	1.4%	1.3%	1.0%	1.8%
TOTAL ML [d]	**6.8%**	**8.2%**	**6.0%**	**5.4%**	**5.2%**	**6.1%**	**4.5%**	**4.3%**	**5.7%**	**6.9%**	**5.0%**	**4.6%**
SHADOW	13.4%	16.1%	10.5%	11.5%	13.3%	16.0%	10.3%	11.3%	13.4%	16.3%	10.3%	11.3%
TOTAL IRREG [e]	**20.3%**	**24.3%**	**16.4%**	**16.8%**	**18.5%**	**22.1%**	**14.8%**	**15.5%**	**19.1%**	**23.2%**	**15.2%**	**15.9%**
Observations	356	168	80	108	356	168	80	108	348	160	80	108

[a] 89 provinces: Como and Lecco excluded from the estimation.
[b] 89 provinces: Forlì-Cesena and Rimini excluded from the estimation.
[c] 87 provinces: Como, Lecco, Forlì-Cesena and Rimini excluded from the estimation.
[d] *TOTAL ML* is computed as the sum of *ML-ENTERPRISE* and *ML-POWER*.
[e] *TOTAL IRREG* is computed as the sum of *TOTAL ML* and *SHADOW*.

An additional interesting result from Table 6 is the substantially unaltered estimates of *SHADOW* when excluding border provinces from the sample. A likely explanation is that proceeds from the shadow economy are easily deposited in Italian banks, because of the loose controls against tax evasion originating from bank and postal account holdings.

[22] This last consideration seems to be consistent with the risk analysis reported in the Annual Report of the Bank of Italy's Financial Intelligence Unit for 2009 (p. 5, English version). The Unit carried out several inspections at local branches due to anomalous financial flows between banks located in Italy and San Marino, and the existence of special agreements between Italian operators and foreign counterparts for the exchange of euro banknotes (p. 28, Italian version). Accordingly, if we drop the provinces close to San Marino, we likely reduce the average level of money laundering activities, since we partly leave out the phenomenon. While in the case of provinces bordering Switzerland there is a possible undetected export of cash, which originates from an incomplete measurement of the true cash in-flows.

3.4.3. Investigating the role of households

A third robustness check is based on the assumption that households and firms use cash in different ways, but our variable *INCASH* sums up the behaviors of these two different operators. In this section we investigate what happens to our money laundering estimates if we consider cash deposited by households only, which represents about 1/3 of the total amount of cash deposited. To this end, we define the variable *INCASH_H*, as the ratio of the value of total cash in-flows by households on current accounts to the value of total non-cash in-flows by households on current accounts. Descriptive statistics in Table A2 confirm the aforementioned assumption: national mean for *INCASH_H* (0.25) is greater than that for *INCASH* (0.14), demonstrating that households use more cash than firms for every traceable euro. This difference is even more observable in Northern regions (0.21 vs. 0.09 for households and firms, respectively), while it almost disappears in the Central regions (0.16 vs. 0.12). Unsurprisingly, when looking at the absolute levels, *INCASH_H* is greater for Southern households (0.37), who rely much more on cash payment than their counterparts in the rest of the country.

Estimates of previous Model 4 considering *INCASH_H* as a dependent variable are shown in Table 7. Despite showing the expected signs, none of the coefficients associated with the legal component of the demand for cash deposits is now significant. On the contrary, coefficients for the money laundering proxies, and especially the coefficients for the shadow economy proxies are highly significant and with the expected signs. However, magnitudes differ from previous results. In particular, coefficients for *EMP_AGR*, *EMP_CON* and *COMM_FRAUD* all increase considerably.

Looking at results in Table 8, we find that households' contribution to the irregular economy is substantial. Considering the complete set of provinces, total money laundered by households amounts to 2.9% of GDP, i.e., about 45% of the total cash laundered via the Italian financial system.[23] The share is even higher when taking into account *ML-POWER*, with households contributing more than 60% of the total; the contribution by households is instead 43% in the case of *ML-ENTERPRISE*. A likely interpretation is that proceeds from extortions can be laundered directly via powerful family clans since they involve relatively

[23] This share and those following have been computed considering baseline estimates in previous Table 2.

small amounts; while proceeds from illegal trafficking, involving large amount of cash, need to pass through (fictitious and running) firms, that operate as a means to reinvest money in the legal economy.

Table 7: Estimates of cash deposit demand [4] considering only cash in-flows by households (*Prais-Winsten regression with PCSE*)

Regressors [a]	**Model 4**
Money laundering component [b]	
ENTERPRISE	0.0560*
[H1]	(1.80)
POWER	0.0170*
[H1]	(1.88)
Structural (legal) component [b]	
YPC	-0.0031
[H5]	(-1.34)
URATE	0.4337
[H6]	(1.58)
ELECTRO	-0.0002
[H7]	(-0.34)
Shadow economy component [b]	
EMP_AGR	1.6476***
[H9]	(7.25)
EMP_CON	1.3723***
[H9]	(4.68)
COMM_FRAUDS	0.0748***
[H10]	(2.98)
Constant	0.0261
	(0.31)
Observations	364
Wald statistic (χ^2)	788.22***
R^2	0.80

[a] Dependent variable: *INCASH_H* = value of total cash payments by households on current accounts normalized to the value of total non-cash payments by households credited to current accounts; z-statistics in parentheses.
[b] Theoretical hypothesis to which each regressor refers is indicated in squared brackets.
***, **, *: Statistically significant at 1%, 5%, 10%, respectively.

Table 8: Size of money laundering and total irregular economy as percentage of GDP (mean 2005-2008) – *PCSE* estimates considering only cash in-flows by households

Model 4	91 provinces [a]				83 provinces [b]			
	ITALY	North	Central	South	ITALY	North	Central	South
ML-ENTERPRISE	2.2%	2.4%	2.1%	2.0%	1.9%	1.9%	2.1%	1.7%
ML-POWER	0.8%	0.6%	0.6%	1.2%	0.6%	0.4%	0.6%	1.1%
TOTAL ML [c]	**2.9%**	**2.9%**	**2.7%**	**3.2%**	**2.5%**	**2.3%**	**2.7%**	**2.8%**
SHADOW	10.4%	11.5%	8.6%	10.1%	8.2%	7.3%	8.6%	9.4%
TOTAL IRREG [d]	**13.4%**	**14.4%**	**11.2%**	**13.2%**	**10.8%**	**9.6%**	**11.2%**	**12.2%**
Observations	364	176	80	108	332	152	80	100

[a] Average values computed using the whole set of money laundering and total irregular economy estimates related to the balanced panel of 91 Italian provinces.

[b] Before computing average values, we discarded all the provinces showing an outlier estimate of *ML-ENTERPRISE*, and/or *ML-POWER*, and/or *SHADOW* in at least one year of the observed period. The 8 outliers were identified using the Hadi (1992, 1994) method and mostly correspond to provinces of medium-small sized towns in North Italy.

[c] *TOTAL ML* is computed as the sum of *ML-ENTERPRISE* and *ML-POWER*.

[d] *TOTAL IRREG* is computed as the sum of *TOTAL ML* and *SHADOW*.

The contribution of households is even more significant in the shadow economy. Considering results on the complete set of provinces, we find that 10.4% of GDP can be attributable to proceeds from legal activities hidden to the Tax Authorities by households, which represents about 4/5 of the total estimated shadow economy in Table 2 (13.4%). This result reflects the structure of the Italian economy, and the importance of small and medium-sized enterprises.

In terms of geographical distribution, we again find that the share of total irregular economy is higher in Northern regions with respect to Southern ones, with the notable exception of *ML-POWER*, for which the occurrence in the South doubles that of the North. But the differences in both *TOTAL ML* and *TOTAL IRREG* across macro-areas are much less pronounced than considering households and firms jointly.

An interesting difference with previous results emerges when dropping outliers, which are the 8 provinces with small and medium-sized cities in the North (like Asti and Reggio Emilia). We find that money laundering estimates are almost unaffected, while the size of the shadow economy falls by more than 2 percentage points at the national level. This decline has to be attributed almost entirely to Northern provinces, for which the *SHADOW* component is now estimated to represent about 7.3% of GDP (against 11.5% when considering the complete set of provinces). The comparison between these results and those referring to cash in-flows by both households and firms (Table 2) suggests that a large sum of cash is laundered via bank and postal accounts payable to firms in large cities, where it is easier to run a fictitious business with the sole purpose of laundering money.

3.4.4. Investigating underreporting in extortions

The fourth robustness check relates to the potential degree of underestimation affecting *detected* crimes with respect to *actual* crimes. This phenomenon can be particularly pronounced in the case of extortions, especially in the South, where criminal syndicates can be so powerful as to dismiss a large portion of prosecutions. The Italian National Institute of Statistics currently produces survey estimates of the degree of underreporting for certain types of crimes, such as thefts and robberies, which show large differences both in the degree and in the geographical distribution of underestimations.[24] However, these official statistics are not available for the two crime categories we consider: illegal trafficking and extortions. We thus resolve to using statistics only for extortions from an unofficial survey conducted by *SOS Impresa* (2011), an association of firms that promotes anti-racketeering and anti-wear initiatives, in order to build up *POWER*2, that is, the number of crimes from extortions reported to the association. This variable can be regarded as a more reliable proxy of *actual* extortions due to the fact that *SOS Impresa* gathers information on an anonymous basis, which implies a lower risk of violent retaliation by the offender and, as a consequence, higher incentive for the victim to report the crime. For simplicity, we will refer to *POWER*2 as *actual* crimes below. Relying on these statistics, underestimation is huge: only 1.2% of extortions reported to *SOS Impresa* has also been detected by judicial authorities at the national level; the ratio drops to 0.7% in the South and is slightly higher in the North (1.5%). Estimates obtained from previous eq. [4] considering *POWER*2 are in Table 9. The coefficient for *POWER*2 turns out to be significant and with the expected sign. The magnitude is similar to that of the coefficient estimated for *POWER* in the previous baseline specification (Model 4 in Table 1). Moreover, the estimates for all the other parameters remain significant and maintain the expected sign.

[24] See the Istat (2010b) report "Reati, vittime e percezione della sicurezza. Anni 2008-2009". Considering bag-snatching, underreporting is larger in North-Western regions (less than 18 incidences reported out of 100 crimes) than in the South. On the contrary, for home thefts underestimation is less pronounced, and – in general – is more severe in the South (73 reports in the North per 100 crimes vs. 47 in the South).

Table 9: Estimates of cash deposit demand [4] using an indicator of *actual* extortions instead of detected extortions (*Prais-Winsten regression with PCSE*)

Regressors [a]	Model 4
Money laundering component [b]	
ENTERPRISE	0.0257***
[H1]	(2.86)
POWER2	0.0078*
[H1]	(1.68)
Structural (legal) component [b]	
YPC	-0.0037***
[H5]	(-2.8)
URATE	0.3950***
[H6]	(2.66)
ELECTRO	-0.0016***
[H7]	(-6.72)
Shadow economy component [b]	
EMP_AGR	0.4438***
[H9]	(4.25)
EMP_CON	0.3084**
[H9]	(2.21)
COMM_FRAUDS	0.0583***
[H10]	(4.88)
Constant	0.1321***
	(2.69)
Observations	364
Wald statistic (χ^2)	34824.55***
R^2	0.91

[a] Dependent variable: *INCASH* = value of total cash payments on current accounts normalized to the value of total non-cash payments credited to current accounts; z-statistics in parentheses.
[b] Theoretical hypothesis to which each regressor refers is indicated in squared brackets.
***, **, *: Statistically significant at 1%, 5%, 10%, respectively.

Table 10: Size of money laundering and total irregular economy as % of GDP (mean 2005-2008) – *PCSE* estimates using an indicator of *actual* extortions instead of detected extortions

Model 4	91 provinces [a]				82 provinces [b]			
	ITALY	North	Central	South	ITALY	North	Central	South
ML-ENTERPRISE	4.8%	6.0%	4.4%	3.2%	3.5%	3.8%	3.6%	3.0%
ML-POWER2	1.3%	0.6%	0.6%	2.9%	1.2%	0.5%	0.6%	2.9%
TOTAL ML [c]	**6.1%**	**6.6%**	**5.0%**	**6.1%**	**4.8%**	**4.3%**	**4.1%**	**5.9%**
SHADOW	11.9%	14.0%	9.3%	10.3%	10.5%	11.4%	8.8%	10.4%
TOTAL IRREG [d]	**18.0%**	**20.6%**	**14.3%**	**16.4%**	**15.3%**	**15.7%**	**13.0%**	**16.3%**
Observations	364	176	80	108	328	148	76	104

[a] Average values computed using the whole set of money laundering and total irregular economy estimates related to the balanced panel of 91 Italian provinces.

[b] Before computing average values, we discarded all the provinces showing an outlier estimate of *ML-ENTERPRISE*, and/or *ML-POWER2*, and/or *SHADOW* in at least one year of the observed period. The 9 outliers were identified using the Hadi (1992, 1994) method and mostly correspond to the provinces of the biggest towns in Central-North Italy.

[c] *TOTAL ML* is computed as the sum of *ML-ENTERPRISE* and *ML-POWER2*.

[d] *TOTAL IRREG* is computed as the sum of *TOTAL ML* and *SHADOW*.

Thus, it is not surprising that national estimates for money laundering reported in Table 10 are largely consistent with those affected by underreporting of crimes (Table 2). Considering the complete set of provinces, the size of money laundering amounts to 6.1% of GDP (vs. 6.4% in our baseline Model 4). Interestingly, the shadow economy component drops by about two percentage points, hence bringing the total irregular economy to 18% of GDP, against 19.8% in the baseline specification. Some differences in terms of money laundering emerge when comparing macro-areas estimates. Firstly, *ML-POWER2* halves in the Northern provinces comparing to national estimates; while it almost doubles in the Southern ones. Since the size of *ML-ENTERPRISE* is substantially unaffected, this almost cancels the differences between the North and the South in the size of cash laundered. Moreover, the decrease in the *SHADOW* component observed at the national level is mostly due to the reduction in Northern provinces (from 15.9% to 14%), while for the Central and the Southern provinces our estimates show a less marked decrease with respect to the baseline specification. Interestingly, underestimating the presence of extortions implies an upward bias for Northern provinces in both the cash laundered (from extortions) and the shadow economy, and a downward bias of cash laundered for Southern ones. This conclusion is further reinforced when eliminating the outliers, which mostly corresponds to the largest Central-Northern cities characterized by a large amount of criminal proceeds stemming from illegal trafficking.

The size of money laundering is now larger for Southern provinces, particularly so for *ML-POWER2* component, which remains at 2.9% of GDP, while *ML-ENTERPRISE* component decreases markedly in the North (from 6% to 3.8%) as expected. Considering also the reduction in the size of the shadow economy mainly due to a much lower value estimated for Northern provinces (11.4% instead of 14%), the total irregular economy is then rather similar between the North and the South of the country.

4. Summary and policy suggestions

In this paper we improve the available estimates of money laundering, almost exclusively derived from data generated by the calibration of theoretical models, by providing a new approach based on an econometric model of the demand of cash deposits. In particular, considering a panel of 91 Italian provinces over the period 2005 to 2008, we separate observed cash in-flows credited on current banking and postal accounts in three different components: (1) a *money laundering* component: the diffusion of both illegal traffics and extortions proves to be an important driver of cash in-flows; (2) a *structural (legal)* component: the average per capita income and the diffusion of electronic payments are negatively associated with cash in-flows, while unemployment rate shows a positive correlation; (3) a *shadow economy* component: the presence of undocumented workers and of commercial tax frauds is positively correlated to cash in-flows.

Starting from these econometric results, we then provide an estimate of the amount of money laundering: we find that the average amount of cash laundered at national level is around 6% of GDP according to our preferred model specification (5% due to illegal trafficking and 1% extortions). This national average hides important differences across macro-areas; focusing on the traditional North-South divide, the share of "dirty money" on GDP is 7.5% in the North against 5.1% in the South. Besides the differences in the amount of cash laundered, the sources of "dirty money" also differ across macro-areas: proceeds to be laundered coming from illegal traffics are almost twice as much in Northern provinces than in Southern ones (6.3% versus 3.4%), while the reverse is true for proceeds from extortions, for which the share in the South is around 1.5 times the value of the North (1.7% versus 1.2%). This evidence is consistent both with the presence of the direct control of local territories based on violence powered by large criminal organizations in the South, and with the ability of these organizations to exploit richer retail markets in the North. Considering also the amount of cash in-flows related to proceeds from the underground production – about 13.5% of GDP – the estimated total amount of money laundered from the irregular sectors ("black" and "grey" economies) is around 20% of GDP and confirms the presence of a marked North-South gradient (23.4% vs. 16.6%), which is driven by the dominance of both illegal trafficking and the shadow economy in the Northern provinces compared to Southern ones. These findings are robust to several robustness checks and, more importantly, are consistent with available evidences of the non-observed economy in Italy obtained in previous studies (e.g., Buehn and Schneider, 2012; Ardizzi *et al.*, 2014).

What policies can we suggest from the above results? The amount of money laundering in the Italian provinces is sizeable. This should be one of the major concerns for governments, since Italy is not among the non-cooperative countries and territories identified by the FATF, and it is certainly not a tax haven that allows setting up anonymous companies. Hence, it is likely that criminal organizations are able to circumvent the KYC rule, even in the presence of strict regulations. Our approach here suggests that criminal organizations provide a considerable amount of cash proceeds that are laundered via the regulated financial and banking system. Hence, an alternative strategy to fight this crime with respect to the transparency rules would be to reduce the attractiveness to untraceable means of payments. In this perspective, limiting the use of cash in transactions would not only be beneficial to improve the efficiency of the payment system, but also to combat this type of crime.

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Appendix. Definition, descriptive statistics and contribution of the different variables included in the equation of cash deposit demand

This study uses a balanced panel of Italian provinces over the period 2005-2008. The dataset merges information of five different sources: *Bank of Italy* (BdI), *Guardia di Finanza* (the Italian Tax Police, GdF), *Istat* (the National Institute of Statistics), *Eurostat* (the European Institute of Statistics), and *SOS Impresa* (a non-profit organization which promotes the development of anti-racketeering and anti-wear initiatives). All monetary variables are provided by BdI. Data on the provincial GDP and unemployment rates are provided by Eurostat and Istat, respectively. The variables used as proxies for the diffusion of commercial tax frauds and undocumented workers are computed on the basis of information provided by GdF and Istat. Finally, the indicators of crime diffusion are computed using data on criminal offenses available from Istat website http://giustiziaincifre.istat.it and from the 2011 Annual Report by *SOS Impresa*. Complete information for all the variables is available for 91 Italian provinces (out of a total of 103).

Table A1. Definition of variables and data source

	Definition	Source
DEPENDENT variable		
INCASH	Ratio of the value of total cash in-flows to the value of total non-cash in-flows on current bank and postal accounts	BdI
INCASH_H	Ratio of the value of total cash in-flows to the value of total non-cash in-flows by households on current bank and postal accounts	BdI
MONEY LAUNDERING variables		
ENTERPRISE	Number of detected crimes (reported to the authorities and resulted in prosecutions) from *drug dealing, prostitution and receiving stolen properties* within the province (divided by its sample mean value and weighted by a GDP concentration index)	Istat and Eurostat
POWER	Number of detected crimes (reported to the authorities and resulted in prosecutions) from *extortion* within the province (divided by its sample mean value and weighted by a GDP concentration index)	Istat and Eurostat
*POWER*2	Number of *actual* crimes (reported to SOS Impresa) from *extortion* within the province (divided by its sample mean value and weighted by a GDP concentration index)	SOS Impresa, Istat and Eurostat
DETECT	Number of reports on irregular financial transactions by the Financial Intelligence Unit of Bank of Italy per thousand current accounts (proxy for the probability of detection)	BdI
STRUCTURAL (LEGAL) variables		
YPC	Per capita provincial GDP	Eurostat
URATE	Provincial unemployment rate	Istat
ELECTRO [a]	Ratio of the value of transactions settled by electronic payments to the total number of current accounts	BdI
INT	Interest rate on current accounts	BdI
SHADOW ECONOMY variables		
EMP_AGR	Share of employment in agriculture (proxy for undocumented workers)	Istat
EMP_CON	Share of employment in constructions (proxy for undocumented workers)	Istat
COMM_FRAUDS	Ratio of the number of detected tax frauds on cash registers and commercial receipts within the province to the number of existing POS (weighted by a GDP concentration index)	GdF, BdI and Eurostat

[a] The numerator of *ELETTRO* is defined by the total value of funds debited from current accounts by the following payment instruments: credit transfers, direct debits, collection item debits, paid checks, card transactions. Geographic distribution is related to the province of the bank or postal branch where the clients or the cardholders hold the current account.

Table A2. Descriptive statistics

Variable	Mean	Standard Deviation Total	*Between*	*Within*	Min	Max
			ITALY [a]			
INCASH	0.143	0.088	0.086	0.017	0.014	0.491
INCASH_H	0.249	0.200	0.194	0.050	0.018	1.570
ENTERPRISE	0.798	0.278	0.274	0.051	0.277	1.992
POWER	1.010	0.789	0.773	0.175	0.171	3.859
*POWER*2	1.174	1.727	1.734	0.036	0.179	7.822
DETECT	0.374	0.155	0.120	0.098	0.070	0.760
YPC (10^3 €)	24.910	5.959	5.901	0.987	12.346	39.082
URATE	0.066	0.039	0.038	0.010	0.019	0.192
ELECTRO (10^4 €)	9.001	6.584	6.033	2.693	1.974	65.717
INT	1.247	0.488	0.265	0.410	0.472	2.909
EMP_AGR	0.050	0.038	0.037	0.009	0.000	0.228
EMP_CON	0.087	0.019	0.017	0.008	0.032	0.144
COMM_FRAUDS	0.204	0.215	0.207	0.063	0.001	1.233

[a] Figures based on a balanced panel of 91 provinces over years 2005-2008 (364 observations).

Variable	Mean	Standard Deviation Total	*Between*	*Within*	Min	Max
			NORTH [a]			
INCASH	0.095	0.051	0.051	0.011	0.014	0.293
INCASH_H	0.212	0.210	0.207	0.047	0.018	1.570
ENTERPRISE	0.732	0.264	0.263	0.041	0.277	1.631
POWER	0.562	0.207	0.178	0.107	0.171	1.242
*POWER*2	0.272	0.051	0.051	0.005	0.179	0.411
DETECT	0.335	0.120	0.088	0.083	0.110	0.640
YPC (10^3 €)	29.193	3.047	2.848	1.146	21.566	39.082
URATE	0.040	0.010	0.008	0.006	0.019	0.074
ELECTRO (10^4 €)	10.623	8.248	7.413	3.743	1.974	65.717
INT	1.290	0.503	0.263	0.430	0.472	2.909
EMP_AGR	0.039	0.027	0.026	0.007	0.000	0.125
EMP_CON	0.081	0.018	0.017	0.007	0.032	0.144
COMM_FRAUDS	0.160	0.217	0.208	0.067	0.001	1.233

[a] Figures based on a balanced panel of 44 provinces over years 2005-2008 (176 observations).

Table A2. Descriptive statistics (continued)

Variable	Mean	Standard Deviation Total	*Between*	*Within*	Min	Max
			CENTRAL [a]			
INCASH	0.116	0.049	0.048	0.013	0.028	0.230
INCASH_H	0.165	0.080	0.070	0.041	0.062	0.454
ENTERPRISE	0.765	0.202	0.203	0.037	0.380	1.249
POWER	0.701	0.213	0.174	0.127	0.271	1.291
POWER2	0.413	0.127	0.129	0.011	0.280	0.882
DETECT	0.401	0.185	0.126	0.138	0.070	0.750
YPC (10^3 €)	26.120	3.014	2.890	1.023	20.612	33.947
URATE	0.057	0.019	0.018	0.007	0.031	0.102
ELECTRO (10^4 €)	8.321	5.540	5.518	1.183	4.136	33.520
INT	1.320	0.510	0.262	0.440	0.476	2.742
EMP_AGR	0.035	0.029	0.028	0.009	0.000	0.128
EMP_CON	0.087	0.018	0.016	0.009	0.054	0.142
COMM_FRAUDS	0.126	0.085	0.079	0.034	0.008	0.399

[a] Figures based on a balanced panel of 20 provinces over years 2005-2008 (80 observations).

Variable	Mean	Standard Deviation Total	*Between*	*Within*	Min	Max
			SOUTH [a]			
INCASH	0.240	0.078	0.074	0.027	0.084	0.491
INCASH_H	0.370	0.190	0.182	0.061	0.108	0.939
ENTERPRISE	0.931	0.302	0.788	0.271	0.458	1.992
POWER	1.970	0.823	0.298	0.070	0.550	3.859
POWER2	3.207	2.039	2.068	0.065	0.428	7.822
DETECT	0.419	0.165	0.143	0.086	0.110	0.760
YPC (10^3 €)	17.034	2.163	2.101	0.621	12.346	22.181
URATE	0.116	0.032	0.028	0.016	0.053	0.192
ELECTRO (10^4 €)	6.860	1.960	1.811	0.808	3.124	11.190
INT	1.123	0.424	0.235	0.355	0.475	2.480
EMP_AGR	0.079	0.042	0.042	0.011	0.000	0.228
EMP_CON	0.098	0.015	0.012	0.009	0.064	0.125
COMM_FRAUDS	0.335	0.224	0.215	0.072	0.037	0.983

[a] Figures based on a balanced panel of 27 provinces over years 2005-2008 (108 observations).

Table A3. Contribution of the variables included in the equation of cash deposit demand (*PCSE* estimates on 91 Italian provinces, mean 2005-2008 – Model 4)

	ITALY	NORTH	CENTRAL	SOUTH
Observed cash deposits (% GDP)	100	100	100	100
Negative contribution:				
YPC	-134	-203	-144	-39
ELECTRO	-19	-30	-17	-5
Positive contribution:				
EMP_CON	29	38	31	16
ENTERPRISE	21	28	23	12
EMP_AGR	19	23	15	16
URATE	19	19	21	19
COMM_FRAUDS	8	9	6	8
POWER	6	5	5	6
Constant	153	211	163	72