ESTIMATING MONEY LAUNDERING THROUGH A "CASH DEPOSIT DEMAND" APPROACH

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Abstract

This paper contributes to the relatively scant literature on money laundering estimation. We propose a new approach focused on the measurement of the "dirty money" pumped into local financial system – through cash deposits at banks – in order to be cleaned up., thus providing an estimation of the size of money laundering at its very early stage. We define a model of "cash deposit demand" which uses as dependent variable the value of cash in-payments on current accounts and includes three types of explicative factors: 1) a structural component, which is expected to capture the legal motivations of cash in-payments; 2) a shadow economy component, so as to capture that part of cash deposit demand related to proceeds from commercial tax frauds and irregular work; 3) a money laundering component, which includes two indicators for the diffusion of criminal activities related to both illegal trafficking (i.e., drug dealing, prostitution, receiving stolen) and exerted power for the control of the territory (i.e., extortions by organized crime). This model of cash deposit demand is estimated on a panel of 91 Italian provinces observed over the period 2005-2008. The size of money laundering is assessed by estimating the "excess demand" for cash in-payments unexplained by structural factors and shadow economy. We find that the average total size of money laundering is around 7% of GDP, 3/4 of which is due to illegal trafficking, while 1/4 is attributable to extortion activities. There are also remarkable differences between Centre-Northern and Southern provinces, in terms of both the overall money laundering size and the relative contributions of the two types of crime.

JEL classification: Money laundering, Cash deposit demand, Shadow economy, Organized crime

Keywords: E41, H26, K42, O17

1. Introduction

(TO BE COMPLETED)

As remarked by Walker & Unger (2009), the economics of money laundering, which aims at exploring the scale and the impact of illicit funds, is a relatively new research field (see, e.g., Tanzi, 1997; Walker, 1999; Masciandaro et al., 2007; Unger, 2007; Schneider, 2010, Schneider and Windischbauer, 2008). Indeed, available information on crime and crime prevention – which is a prerequisite for this type of study – has improved substantially only in the last two decades, due to the strong support by the Financial Action Task Force (FATF), an intergovernmental body created in 1989 by the G7 to fight money laundering and terrorism financing. By allowing "dirty money" to be cleaned up via the regular financial system, money laundering plays the fundamental role of making effective the potential reinvestment of illicit proceeds in the legal economy.

We aim at contributing to existing literature on money laundering estimation by proposing a new method focused on the measurement of the *flows of illicit cash* pumped into the financial system, thus providing an estimation of the size of money laundering economy at its *very early stage*.

The recent theoretical model proposed by Barone and Masciandaro (2011) identifies the macro relations between criminal profits, money laundering and legal investments. Interestingly, the authors point to the dynamic dimension of the link between criminal revenues and legal investments. In sum, an initial criminal activity produces dirty profits. The (costly) laundering process allows to re-invest in the legal sector of the economy the share of such profits that minimizes the risks of prosecution. As the authors point out, «The share which is destined to the illegal sector will produce further dirty revenues which will have undergo the laundering process; the money laundering cycle is therefore in motion and each step – provided that no obstacle hinders the process – contributes to increase the legal assets held by the criminal sector» (p. 124). The authors, however, focus on criminal revenues which are the proceeds of the specific crime of drug traffic, claiming that «drug trafficking remains a priority in criminal markets» (p. 125). As we will discuss in Section 2.1, we believe that is preferable – with particular reference to the Italian case – to rely on a broader definition of criminal activities, using the two concepts of "power syndicate" and "enterprise syndicate" borrowed by the crime literature (Block, 1980)

To the best of our knowledge, available empirical evidence on Italy do not include estimates of money laundering based on econometric models using observed data. Existing literature seems to have exclusively focused on data generated by the calibration of theoretical models so far. Although following a different approach, the model proposed by Argentiero *et al.* (2008) share a common feature with Barone and Masciandaro (2011): money laundering plays the economic function of linking the criminal economy to the formal economy by turning illegal profits of the former into legal investments in the latter. Argentiero *et al.* (2008) deal with a micro founded two sector dynamic general equilibrium model calibrated to generate money laundering time series from 1981 to 2001. As a result, money laundering accounts for approximately 12% of aggregate GDP. However, as pointed out by Barone and Masciandaro (2011), the authors seem to muddle up shadow economy and money laundering activities, which are two linked, but different, phenomena.

2. Defining cash deposit demand and testable hypotheses

We define a model of demand for cash deposit services, using as dependent variable the ratio of the value of total cash in-payments on current (bank and postal) accounts to the value of total non-cash in-payments credited to current (bank and postal) accounts (*INCASH*).

In order to disentangle the "dirty money" component of cash in-payments, we estimate a full model which controls for alternative sources of cash deposit demand, i.e., linked to official and shadow economic activities. As clarified below, this empirical strategy allows us to evaluate the excess demand for cash deposits due to money laundering.

In the following we present our methodological approach and formulate testable hypotheses.

2.1. The dirty money component of cash deposit demand

Money laundering can be regarded as a criminal offense which results from other underlying criminal activities that amplifies in a cumulative way the impact of crime on both regular and irregular economies. The definition of recycling implies that the income stemming from a crime needs to be "cleaned up" through the legal channel (e.g., bank transactions) in order to lower the likelihood for the criminal agent of being caught. After this, the "cleaned up" money can be reinvested in legal activities.

Following Schneider and Windischbauer (2008), the main stages in money laundering process can be summarized as follows:

a) PLACEMENT: «At the first initial stage termed placement, ill-gotten gains from punishable preactions are infiltrated into the financial system; at this junction there is an increased risk of being revealed»;
b) LAYERING: «By dint of the so called layering stage, 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: «In this third stage 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».

Our estimation strategy will cover step a). As a consequence, our measures of dirty money can be interpreted as a *lower bound* of the whole size of money laundering economy within a country computed at the provincial level. This figure will then be more or less enlarged in the following global-level stages (i.e., layering and integration) according to the number of transactions carried out in the attempt to well conceal the source of illegal income and to address it towards profitable investments.

Two preliminary steps deserve a brief discussion, that is: the definition of the types of criminal activities that generate illegal profits to be cleaned up, and the related issue of the selection of the variables aimed to capture their diffusion at the provincial level.

As for the definition of criminal activities, we rely on the distinction originally proposed by Block (1980) – well established within the literature on organized crime – between "enterprise syndicate" and "power syndicate". The former concept refers to criminal groups running illegal economic activities such as drug trafficking, smuggling, prostitution and so on, 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 for Italy, where organized crime has "headquarters" predominantly localized in the South, while the "retail markets" for goods and services such as drug and prostitution prove to be more lucrative in the richest regions of the country, that is, in the Centre-North (Ardizzi *et al.*, 2012).

The relative presence of "power syndicate" at the provincial level is measured by the number of detected crimes from extortion activity within the province divided by its sample mean value (*POWER*). The choice to focus on extortion is motivated by the fact that this is the main instrument used be criminal organization to gain the control of the local territories. For instance, Gambetta (1993) points out that the Sicilian Mafia uses extortion as «an industry which produces, promotes, and sells private protection». The request for protection is made regardless of the will of the individual, and using his words «whether one wants or not, one gets it and is required to pay for it». The same argument applies the other Italian regions traditionally dominated by criminal organizations, such as the Camorra in Campania, the 'Ndrangheta in Calabria, and the Sacra Corona Unita in Puglia[1].

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

Both *ENTERPRISE* and *POWER* variables are weighted by a GDP concentration index. Such a standardization allows us to better compare provinces characterized by remarkable differences in the level of socio-economic development and perhaps in the effort of crime detection and contrasting, thus avoiding attaching automatically higher levels of crime and money laundering to provinces with a number of detected offences above the sample mean.

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

Both indicators for the diffusion of criminal activities are expected to show positive correlations with cash in-payments. Thus, we put forward our first hypothesis:

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

2.2. The role of legal motivations and shadow economy proceeds

In order to control for the determinants of *INCASH* other than money laundering, our model includes a set of variables expected to capture the legal motivations of cash deposit demand, as well as its component linked to shadow economy proceeds.

As for the legal motivations, we introduce the following controls: the degree of local socio-economic development; the interest rate on bank deposits; the diffusion of electronic payment instruments in commercial transactions. 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 resort to cash for payments, thus the lower should be the demand for cash deposits. The average income is highly correlated with 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 measure of socio-economic development is per capita provincial GDP (*YPC*) and the related hypothesis to be tested is the following:

H2: *The higher the average per capita income of a province, the lower is the demand for cash deposits, ceteris paribus.*

We also consider the rate of unemployment at the provincial level (*URATE*) as a second possible indicator for the state of the economic development. In particular, to some extent this variable reflects differences in income distribution (see, e.g., Brandolini *et al.*, 2004), thus in educational levels, and is expected to exert a positive impact on the use of cash for payments, thus on the demand for cash deposits: for a given average value of per capita GDP, a higher unemployment rate corresponds to a 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. We formulate then the following hypothesis:

H3: *The higher the unemployment rate of a province, the higher is the demand for cash deposits, ceteris paribus.*

A further control is needed in order to capture the variability across provinces of the average attitude towards the use of cash in transactions in alternative to electronic means of payment. Several studies (e.g., Drehmann and Goodhart, 2000; Goodhart and Krueger, 2001; Schneider, 2009) emphasize the importance of the technology of payments, with a particular reference to the supply of electronic instruments. In line with this literature, we account for available technology of payments 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 settled 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 cash deposit demand. Thus, the expected sign of the *ELECTRO* coefficient is negative.

H4: *The higher the diffusion of electronic payments in commercial transactions, the lower is the demand for cash deposits, ceteris paribus.*

Finally, we consider the interest rate on current deposits (*INT*) as a possible determinant of the legal component of *INCASH*. 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 currency. Thus, due to the usual "speculative" motive, the expected sign of *INT* should be positive. However, there exist at least four reasons why this could not be the case. First, *INCASH* is defined by a share, which implies that a higher interest rate could in principle impact proportionally both on its denominator and numerator, leading to a null the overall effect. Second, our model deals with cash in-payments (a flow variable) rather than stock values of deposits, which implies an ambiguous effect of the interest rate[2]. Furthermore, the years covered by our estimations have been characterized by very low interest rates, which is likely to have strongly mitigated the speculative motive (ECB, 2008). Finally, we notice that most recent developments in innovative banking (i.e. internet banking) – saving on operational costs and offering interest rates higher than

[2] For a more detailed discussion on recent trends of both flow and stock monetary aggregates in Italy see Ardizzi *et al.* (2012).

traditional banking – might bring about a negative relationship between *INT* and cash deposits. Given these considerations, the expected sign of the *INT* coefficient is a priori unclear and we do not formulate an expectation on its sign.

The indicators used for controlling cash in-payments linked to shadow economy proceeds at the provincial level are the sectorial composition of local economies' production and the diffusion of tax frauds in sales by commercial retailers.

The sectorial composition of the production has been found to significantly affect the size of shadow economy (e.g., Johnson *et al.*, 2000). Employment shares in agriculture (*EMP_AGR*) and construction industry (*EMP_CON*) are variables traditionally used as proxies for the evasion of income tax and social security contributions, being these the typical sectors with a higher presence of irregular workers (e.g., Torgler and Schneider, 2009; Capasso and Jappelli, 2011). As for Italy, according to the recent estimates provided by ISTAT (2010), irregularly employed workers in 2009 were 12.2% of total employed workforce, and the phenomenon was particularly concentrated in agricultural (24.5%) and construction sectors (10.5%). Thus, we formulate the following hypothesis:

H5: *The larger the employment in agricultural and construction sectors, the higher is the number of irregular workers and the demand for cash deposits due to shadow economy proceeds, ceteris paribus.*

Finally, we include in our model a variable controlling for irregularities detected by 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 (lower where the number of POS is higher, see Ardizzi *et al.*, 2012). This ratio is weighted by a GDP concentration index for the same reason discussed above for crime variables.

H6: *The higher the diffusion of commercial tax frauds, the higher is the demand for cash deposits due to shadow economic proceeds, ceteris paribus.*

2.3. The assessment of money laundering size

Equation [1] below provides the complete model of cash deposit demand to be estimated, which consider cash in-payments due to money laundering, controlling also for the role of legal (or structural) motivations and shadow economy proceeds:

$$INCASH_{it} = \alpha_0 + \alpha_1 YPC_{it} + \alpha_2 URATE_{it} + \alpha_3 ELECTRO_{it} + \alpha_4 INT_{it} + \alpha_5 EMP\_AGR_{it} + \alpha_6 EMP\_CON_{it} + \alpha_7 COMM\_FRAUDS_{it} + \alpha_8 ENTERPRISE_{it} + \alpha_9 POWER_{it} + \varepsilon_{it} \quad [1]$$

In analogy with the reinterpretation of the Currency Demand Approach proposed in Ardizzi *et al*. (2012), the size of money laundering economy is assessed by estimating the "excess demand" for cash deposits unexplained by structural factors and shadow economy activities. This excess demand is obtained as the difference between the fitted values of *INCASH* from the full model [1] and the predicted values obtained from a restricted version of Equation [1] where the coefficients of *ENTERPRISE* and *POWER* are set equal to zero. To evaluate separately the size of the two components of dirty money, we then proceed in a similar manner, by imposing alternatively the restrictions $\alpha_8 = 0$ and $\alpha_9 = 0$ and calculating the excess demand for cash deposits due to illegal traffics and criminal activities linked to territory control, respectively. Given our definition of *INCASH*, money laundering estimates obtained with this procedure are expressed in relation to total deposits ordered by instruments other than cash. Thus, in order to have measures comparable with previous studies, we need to rescale our results and express them in terms of provincial GDP.

In the 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 money laundering component in the South. On the other hand, given the ability of criminal organizations to "export" illegal traffics in the richest areas of the country, where the demand for "goods and services" such as drug and prostitution is presumably higher, we expect to find a larger size of *ENTERPRISE* components in the Centre-North. We formulate then this last hypothesis:

H7: *The incidence of money laundering component due to ENTERPRISE is relatively higher in the Centre-North, while the component due to POWER is relatively higher in the South.*

3. Econometric analysis

3.1. Data and estimation methodology

The model of cash deposit demand described by Equation [1] 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 Italian provinces (103), and are those for which complete information were available for all the variables in Equation [1]. The Appendix reports the definition and descriptive statistics (for the whole sample, as well as for the two macro-areas, Centre-North and South, separately) and information about the different data sources (see Tables A1 and A2).

As for the estimation methodology, given the panel structure of our data and the marked heterogeneity across units (as highlighted by the prevalence of the *between* component of standard deviation for all the variables excepting *INT*, see Table A2), we preliminary 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 subjects can lead to biased statistical inference (Cameron and Trivedi, 2005). However, while most recent studies provide standard error estimates that are heteroskedasticity- and autocorrelation consistent, cross-sectional or "spatial" dependence in the residuals is still often ignored, thus imposing an artificial and potentially distorsionary constraint on empirical models. Indeed, relying on proper statistical tests, we found that all the three phenomena are present in the error structure of our data [3]. Therefore, in order to adjust the standard errors appropriately, we decided to apply the OLS estimator with Panel-Corrected Standard Errors (*OLS PCSE*) suggested by Beck and Katz (1995). In particular, we specify that, within groups, there is first-order autocorrelation and that the coefficient of the AR(1) process is specific to each group (see Hoechle, 2007) [4].

[3] Specifically, we used the Wooldridge (2002) test for autocorrelation in panel data, the Greene (2000) test for 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.

[4] Estimations have been carried out using the Stata command *xtpcse* with the option *corr(psar1)*.

Table 1: Estimates of cash deposit demand: 91 Italian provinces, 2005-2008 (*OLS with Panel-Corrected Standard Errors*)

Regressors [a]	Model 1	Model 2	Model 3
YPC	-0.0067***	-	-0.0044***
	(-5.03)	-	(-3.06)
URATE	-	0.6542***	0.3836***
	-	(6.87)	(2.62)
ELECTRO	-0.0012***	-0.0021***	-0.0015***
	(-3.56)	(-8.98)	(-5.92)
INT	0.0006	-0.010***	-0.0019
	(0.20)	(-7.71)	(-0.73)
EMP_AGR	0.5658***	0.6080***	0.5104***
	(7.73)	(7.55)	(4.97)
EMP_CON	0.3588***	0.4519***	0.3320***
	(3.01)	(3.00)	(2.24)
COMM_FRAUDS	0.0479***	0.0763***	0.0605***
	(3.58)	(8.18)	(5.21)
ENTERPRISE	0.0312***	0.0272***	0.0268***
	(3.34)	(2.52)	(2.72)
POWER	0.0121***	0.0143***	0.0088*
	(2. 49)	(2.92)	(1.83)
Constant	0.2107***	0.0054	0.1405***
	(4.47)	(0.46)	(2.63)
Observations	364	364	364
Wald statistic (χ^2)	1590.86***	3658.13***	5004.28***
R^2	0.92	0.91	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 round brackets. ***, **, * : statistically significant at 1%, 5%, 10%.

3.2. Estimates of cash deposit demand equation

Table 1 reports parameter estimates of Equation [1] according to three different specifications, where only *YPC* (Model 1), or *URATE* (Model 2), or both (Model 3) are included as control variables for the demand of cash deposits linked to the degree of socio-economic development. All the models perform quite well in terms of fit (the Wald statistic is always significant at 1% and the R^2 value is above 0.90) and show coefficients that are statistically significant and with signs consistent with our theoretical hypotheses H1-H6.[5] The results confirm that cash deposit demand is driven by: 1) a structural (legal) component, where the average per capita income (*YPC*) and the diffusion of electronic payments (*ELECTRO*) have a negative impact on cash in-payments, while the unemployment rate (*URATE*) shows a positive correlation; 2) a shadow economy component, where the two proxies for irregular work (*EMP_AGR* and *EMP_CON*) and the presence of commercial tax frauds (*COMM_FRAUDS*) positively affect cash in-payments; 3) a money laundering component, where both the diffusion of illegal traffics (*ENTERPRISE*) and of extortion activities (*POWER*) prove to be important explicative factors of cash in-payments.

It is worth noticing that both indicators for the state of local economy remain highly significant when used jointly (Model 3). This supports our argument that the unemployment rate captures an additional (distributional) dimension of socio-economic development besides the average per capita income [6], which helps better control for the legal motivations of cash deposit demand. An interesting finding is highlighted by Table A3 and Figure A1 in the Appendix, which report the average simulated contribution of each variable to the observed demand for cash deposits (expressed in % of GDP and normalized to 100), by referring to the most complete specification of Equation [1] (Model 3). The major (negative) role is played by the level of per capita GDP, while all the other regressors account for a much lower share of cash deposit demand. The predicted contributions also points to sensible differences across macro-areas. In particular, the incidence of *YPC* decreases (in absolute value) from 160 in the Centre-North to only 34 in the South, becoming relatively more close to the share of *URATE* (19), which is a not surprising result given the greater relevance of unemployment issue in southern regions; furthermore, in accordance with our hypothesis H7, the *ENTERPRISE* component of criminal activities shows a much higher incidence in the Centre-North than in the South (26 vs. 12), while the inverse is observed for the share of *POWER*, although with a less marked gap (6 vs. 7).

[5] The only exception is the interest rate on bank deposits (*INT*), which shows no significant correlation or a negative correlation with cash in-payments. Possible motivations for this evidence have been discussed in Section 2.2.

[6] Regarding the joint use of the two variables see also Buehn and Schneider (2012).

Table 2: Size of money laundering as % of GDP (mean 2005-2008) – *OLS PCSE* estimates

Model 1	91 provinces [a]			83 provinces [b]		
	ITALY	CENTRE-NORTH	SOUTH	ITALY	CENTRE-NORTH	SOUTH
TOTAL	8.0%	8.6%	6.9%	6.3%	6.2%	6.4%
ENTERPRISE	*5.8%*	*6.7%*	*3.9%*	*4.4%*	*4.7%*	*3.6%*
POWER	*2.2%*	*1.9%*	*3.0%*	*1.9%*	*1.5%*	*2.8%*
Obs.	364	256	108	332	228	104
Model 2	**91 provinces [a]**			**83 provinces [b]**		
	ITALY	CENTRE-NORTH	SOUTH	ITALY	CENTRE-NORTH	SOUTH
TOTAL	7.7%	8.0%	6.9%	6.0%	5.9%	6.5%
ENTERPRISE	*5.1%*	*5.8%*	*3.4%*	*3.8%*	*4.1%*	*3.2%*
POWER	*2.6%*	*2.2%*	*3.5%*	*2.2%*	*1.8%*	*3.3%*
Obs.	364	256	108	332	228	104
Model 3	**91 provinces [a]**			**83 provinces [b]**		
	ITALY	CENTRE-NORTH	SOUTH	ITALY	CENTRE-NORTH	SOUTH
TOTAL	6.6%	7.1%	5.4%	5.1%	5.1%	5.1%
ENTERPRISE	*5.0%*	*5.7%*	*3.3%*	*3.7%*	*4.0%*	*3.1%*
POWER	*1.6%*	*1.4%*	*2.1%*	*1.4%*	*1.1%*	*2.0%*
Obs.	364	256	108	332	228	104

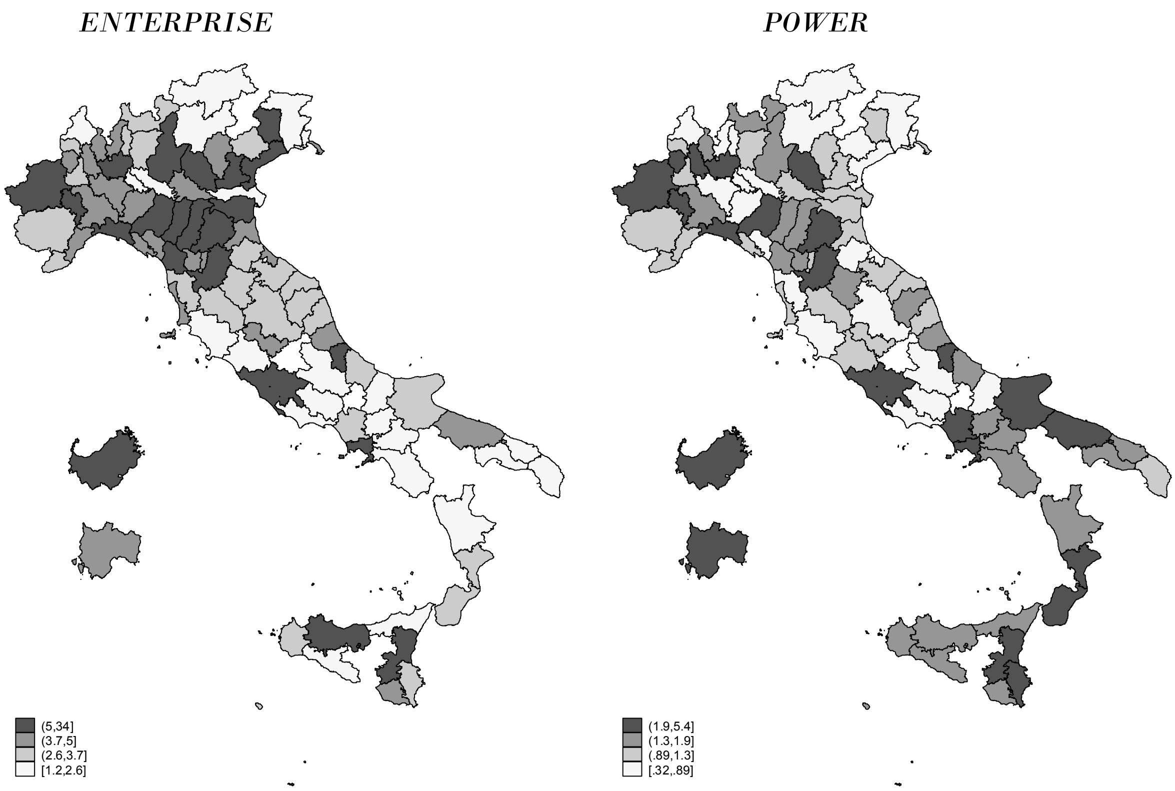
[a] Average values computed using the whole set of money laundering estimates related to the balanced panel of 91 Italian provinces.

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

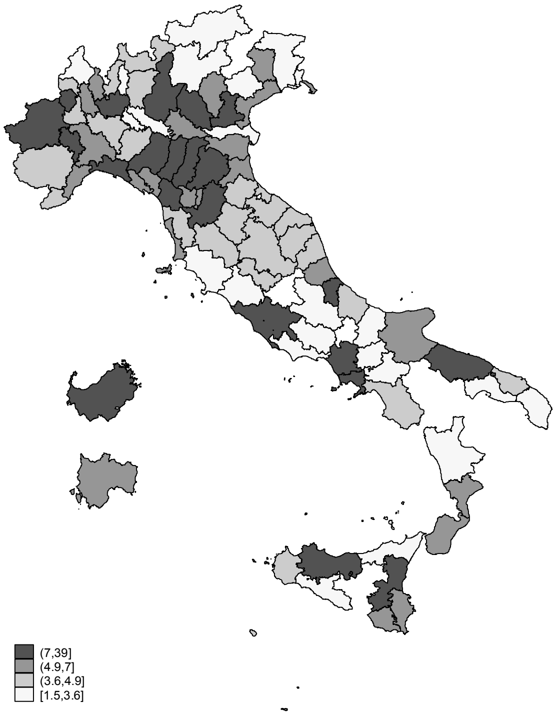
3.3. Estimates of money laundering size

The size of money laundering economy for each province in each year has been assessed relying on the three model specifications discussed above and computing separate measures for *ENTERPRISE* and *POWER* components. Table 2 shows the average values – for Italy and for the two sub-samples of provinces located in the Centre-North and in the South – obtained using the whole set of money laundering estimates for the 91 provinces, as well as discarding 32 outlier estimates, related to 8 provinces identified applying the Hadi (1992, 1994) method with respect to the two components jointly considered. Notice that outliers mostly correspond to the provinces of the biggest (and the richest) towns in the Centre-North – like Rome, Milan and Turin – and are mainly driven by the *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 drug, prostitution and receiving stolen are more lucrative (Ardizzi *et al.*, 2012).

Figure 1: Geographical distribution of money laundering size as a % of GDP by province (*OLS PCSE* estimates on 91 Italian provinces, mean 2005-2008 – Model 3)



TOTAL



Several interesting results emerge looking at Table 2. First, the estimated size of total money laundering ranges from 6.6% of GDP with Model 3 to around 8% when using the restricted specifications of Equation [1] 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 state of local economies (i.e., average per capita income and its distribution across the population), one could mistakenly attribute to money laundering a part of cash deposit demand linked to legal transactions. Notice also that, according to our estimation strategy discussed in Section 2.1, these lower values compared to those obtained in previous studies on Italy (e.g., around 12% in Argentiero *et al.*, 2008), are justified by the fact that here we are focusing on the PLACEMENT stage of money laundering process, i.e., when the illicit cash is pumped into the local financial system. Our measures can then be interpreted as lower bounds of the whole size of money laundering, which will be enlarged in the following global-level stages of LAYERING and INTEGRATION (Schneider and Windischbauer (2008).

Second, in all models the estimates at national level highlight that the major role is played by the *ENTERPRISE* component of criminal activities. In particular, according to the most complete specification of cash deposit demand (Model 3), about 3/4 of dirty money share is attributable to illegal trafficking (5%), while 1/4 is due to *POWER* (1.6%). However, looking at the estimates disaggregated at macro-area level, there are remarkable differences between Centre-Northern and Southern provinces in terms of both the total 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 7.1% in the Centre-North against 5.4% in the South; as for the incidence of *ENTERPRISE* and *POWER*, the former in Centre-Northern provinces is about 1.7 times higher than in Southern ones (5.7% vs. 3.3%), while the inverse is true for money laundering coming from extortion activities, for which the share in the South is 1.5 times the value of the Centre-North (2.1% vs. 1.4%). This provides further support to our argument in hypothesis H7 of a greater incidence of illegal trafficking proceeds in the richest areas of the countries and of proceeds from the direct control of the territory through the power in the regions traditionally dominated by the big criminal organizations, such as Mafia, Camorra, 'Ndrangheta, and Sacra Corona Unita. This picture emerges also from Figure 1, which shows the geographical distribution of money laundering by province, both as *TOTAL* size and distinguishing *ENTERPRISE* from *POWER*.

Figure 1 also points to the marked variability across provinces within the two macro-areas, which embrace situations with very low values (white zones) and cases with very high values (dark gray zones). This is particularly evident for the distribution of *ENTERPRISE* component in the Centre-North, where it clearly emerges the polarization of the phenomenon in some provinces, including the biggest towns such ad Milan, Turin, Genoa, Bologna and Rome. This helps explain why considering the average values obtained on 83 provinces, i.e., by discarding the estimates with outlier values for *ENTERPRISE* and *POWER* shares, the overall size of money laundering decreases significantly (from 6.6% to 5.1% in Model 3) and also the gap between macro-areas tends to disappear, mainly as a consequence of the lower incidence of *ENTERPRISE* component in the Centre-North (which reduces to 4%).

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

Regressors [a]	**Model 3**
YPC	-0.0061***
	(-6.35)
URATE	0.2733***
	(2.87)
ELECTRO	-0.0011***
	(-3.43)
INT	0.0018
	(0.59)
EMP_AGR	0.4079***
	(4.51)
EMP_CON	0.2614***
	(2.31)
COMM_FRAUDS	0.0284**
	(2.11)
ENTERPRISE	0.0287**
	(2.25)
POWER	0.0099**
	(2.05)
Constant	0.2034***
	(6.16)
Observations	364
Wald statistic (χ^2)	369.11***
σ_u	0.0380***
	(11.38)
σ_e	0.0189***
	(22.82)
ρ	0.8026
	(25.50)

[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.

***, **, * : statistically significant at 1%, 5%, 10%.

3.4. Robustness analysis

As a robustness check of our findings, we estimate again Equation [1] using a Tobit regression with Random Effects (*Tobit RE*), in order to explicitly account for unobservable residual heterogeneity across provinces. This model has the advantage – as compared to a standard panel regression with random effects – to accommodate for the particular distribution of our dependent variable, which is censored at zero (Wooldridge, 2002). In particular, we specify the error structure of Equation [1] as $\varepsilon_{it} = u_i + e_{it}$, where u and e are individual effects and the standard disturbance term, respectively.

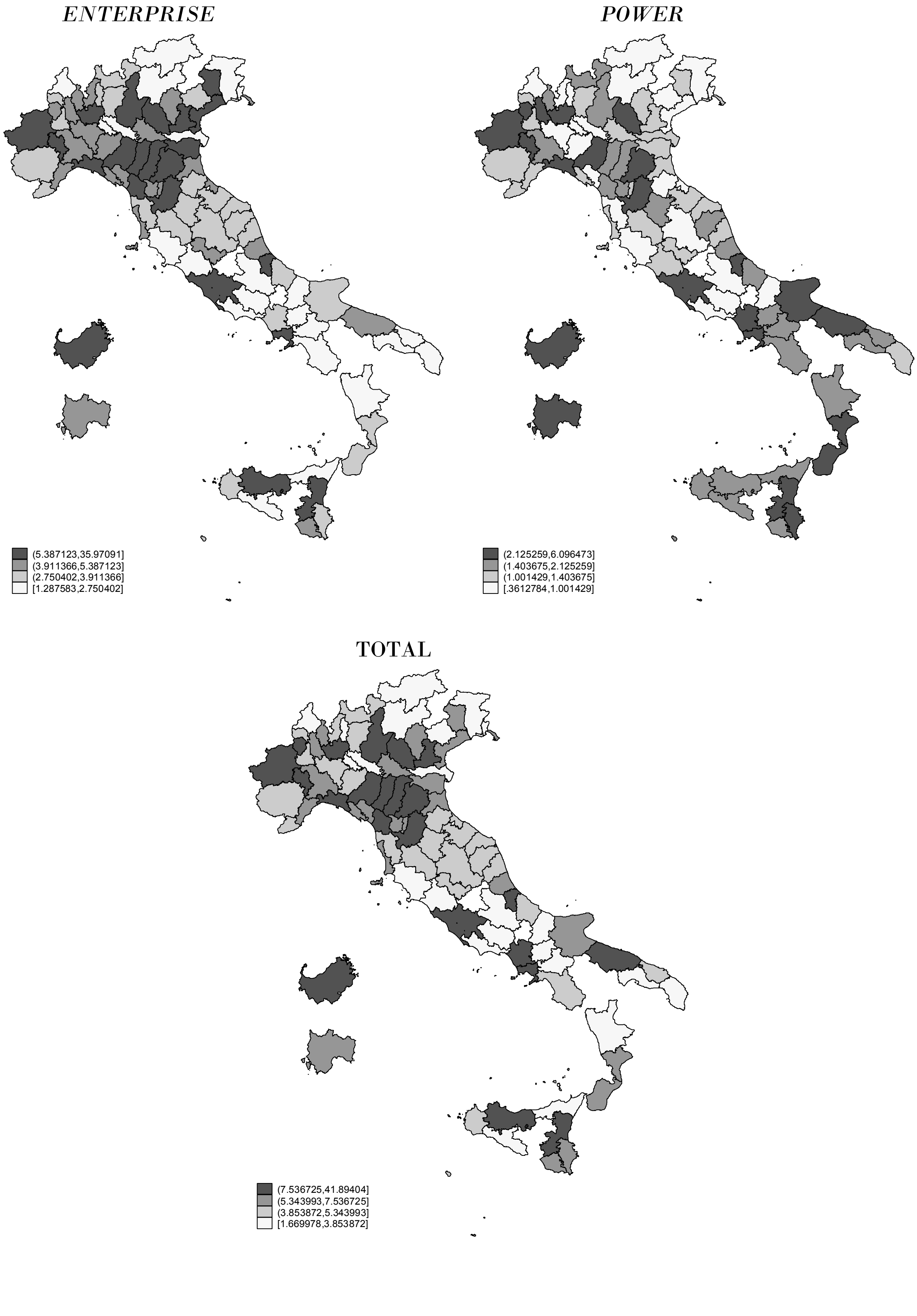
Table 4: Size of money laundering as % of GDP (mean 2005-2008) – *Tobit RE* estimates

Model 3	91 provinces [a]			83 provinces [b]		
	ITALY	CENTRE-NORTH	SOUTH	ITALY	CENTRE-NORTH	SOUTH
TOTAL	7.2%	7.7%	6.0%	5.7%	5.5%	5.7%
ENTERPRISE	*5.4%*	*6.1%*	*3.6%*	*4.1%*	*4.3%*	*3.4%*
POWER	*1.8%*	*1.6%*	*2.4%*	*1.6%*	*1.2%*	*2.3%*
Obs.	364	256	108	336	228	104

[a] Average values computed using the whole set of money laundering 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 the *POWER* and/or the *ENTERPRISE* component in at least one year of the observed period. The 8 outliers were identified using the Hadi (1992, 1994) method and mostly correspond to the provinces of the biggest towns in Centre-North Italy.

Tables 3 and 4 show coefficient estimates and money laundering measures for Model 3, respectively. The results are consistent with those discussed in previous section, confirming all our hypotheses H1-H7. More precisely, the average total size of money laundering is around 7% if computed using the whole set of estimates related to 91 provinces, and reduces to 5.7% for the restricted sample of 83 provinces which excludes outlier values of *ENTERPRISE* and *POWER*. We find again a major role played by *ENTERPRISE* and a sensible gap between macro-areas, with the provinces in the Centre-North showing a higher value (7.7% vs. 6%) due to the much stronger incidence of *ENTERPRISE* component (6.1% vs. 3.6%), while those in the South exhibit a relatively higher share for *POWER* (2.4 vs. 1.6%). Finally, Figure 2 confirms the marked variability across provinces within each macro-area, as well as the polarization of money laundering in certain provinces, which is particularly evident for the values of *ENTERPRISE* related to the biggest (and richest) towns in the Centre-North.

Figure 2: Geographical distribution of money laundering size as a % of GDP by province (*Tobit RE* estimates on 91 Italian provinces, mean 2005-2008 – Model 3)



4. Conclusions and policy implications

(TO BE COMPLETED)

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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 four different sources: *Bank of Italy* (BdI), *Guardia di Finanza* (the Italian Tax Police, GdF), Istat (the National Institute of Statistics), and Eurostat (the European Institute of Statistics). All monetary variables are provided by BdI. Data on the provincial GDP and unemployment rate are provided by Eurostat and Istat, respectively. The variables used as proxies for the diffusion of commercial tax frauds and irregular work are computed on the basis of information provided by GdF and Istat. Finally, the indexes of crime diffusion are computed using data on criminal offences available from Istat website http://giustiziaincifre.istat.it. Complete information for all the variables are available for 91 Italian provinces (out of a total of 103).

Table A1. Definition of variables and data source

	Definition	Source
CONTROL variables		
INCASH	Ratio of the value of total cash in-payments on current (bank and postal) accounts to the value of total non-cash in-payments credited to current (bank and postal) accounts	BdI
YPC	Per capita provincial GDP	Eurostat
URATE	Provincial unemployment rate	Istat
ELECTRO	Ratio of the value of transactions settled by electronic payments to the total number of current accounts	BdI
INT	Rate of interest on current accounts	BdI
EMP_AGR	Share of employment in agriculture (proxy for irregular work)	Istat
EMP_CON	Share of employment in constructions (proxy for irregular work)	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 (divided by its sample mean value and weighted by a GDP concentration index)	GdF, BdI and Eurostat
CRIME variables		
ENTERPRISE	Number of crimes from *drug dealing, prostitution and receiving stolen* within the province (divided by its sample mean value and weighted by a GDP concentration index)	Istat and Eurostat
POWER	Number of crimes from *extortion activity* within the province (divided by its sample mean value and weighted by a GDP concentration index)	Istat and Eurostat

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
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
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
			CENTRE-NORTH [b]			
INCASH	0.102	0.052	0.051	0.011	0.014	0.293
YPC (10^3 €)	28.232	3.350	3.181	1.107	20.612	39.082
URATE	0.045	0.016	0.015	0.006	0.019	0.102
ELECTRO (10^4 €)	9.903	7.572	6.917	3.170	1.974	65.717
INT	1.299	0.504	0.261	0.432	0.472	2.909
EMP_AGR	0.038	0.027	0.027	0.007	0.000	0.128
EMP_CON	0.083	0.018	0.017	0.008	0.032	0.144
COMM_FRAUDS	0.149	0.186	0.178	0.059	0.001	1.233
ENTERPRISE	0.742	0.246	0.244	0.040	0.277	1.631
POWER	0.605	0.218	0.187	0.114	0.171	1.291
			SOUTH [c]			
INCASH	0.240	0.078	0.074	0.027	0.084	0.491
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
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

[a] Figures based on a balanced panel of 91 provinces over years 2005-2008 (364 observations).
[b] Figures based on a balanced panel of 64 provinces over years 2005-2008 (256 observations).
[c] 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 (*OLS PCSE* estimates on 91 Italian provinces, mean 2005-2008 – Model 3)

	ITALY	CENTRE-NORTH	SOUTH
Observed cash deposits (% GDP)	100	100	100
YPC	-115	-160	-34
ELECTRO	-20	-28	-5
INT	-2	-3	-1
Constant	135	176	64
EMP_CON	26	33	14
ENTERPRISE	21	26	12
EMP_AGR	20	21	17
URATE	20	20	19
COMM_FRAUDS	9	9	8
POWER	7	6	7
Observations	364	256	108

--- positive contribution
--- negative contribution

Figure A1. Contribution of the variables included in the equation of cash deposit demand (*OLS PCSE* estimates on 91 Italian provinces, mean 2005-2008 – Model 3)