BANCA D'ITALIA
EUROSISTEMA

Unità di Informazione Finanziaria per l'Italia

Quaderni dell'antiriciclaggio

Analisi e studi

Cash payment anomalies and money laundering: An econometric analysis of Italian municipalities

Guerino Ardizzi, Pierpaolo De Franceschis e Michele Giammatteo

gennaio 2016

numero 5

BANCA D'ITALIA
EUROSISTEMA

Unità di Informazione Finanziaria per l'Italia

Quaderni dell'antiriciclaggio

Analisi e studi

Cash payment anomalies and money laundering: An econometric analysis of Italian municipalities

Guerino Ardizzi, Pierpaolo De Franceschis e Michele Giammatteo

Numero 5 gennaio 2016

La serie Quaderni dell'antiriciclaggio *ha la finalità di presentare dati statistici, studi e documentazione su aspetti rilevanti per i compiti istituzionali della UIF — Unità d'Informazione Finanziaria per l'Italia, Banca d'Italia.*

La serie si articola in due collane: la collana Dati statistici *presenta, con periodicità semestrale, statistiche sulle segnalazioni ricevute e informazioni sintetiche sull'operatività dell'Unità; la collana* Analisi e studi *comprende contributi sulle tematiche e sui metodi in materia di contrasto al riciclaggio e al finanziamento del terrorismo.*

La collana Analisi e studi *comprende lavori realizzati all'interno della UIF, talvolta in collaborazione con altri settori della Banca d'Italia o con Istituzioni esterne. I lavori pubblicati riflettono esclusivamente le opinioni degli autori, senza impegnare la responsabilità delle Istituzioni di appartenenza.*

Unità di Informazione Finanziaria
per l'Italia

Direttore responsabile
Claudio Clemente

Per la pubblicazione cartacea:
autorizzazione del Tribunale di Roma n. 1942013 del 30 luglio 2013
Per la pubblicazione telematica:
autorizzazione del Tribunale di Roma n. 1932013 del 30 luglio 2013

ISSN 2283-3498 (stampa)
ISSN 2283-6977 (online)

CASH PAYMENT ANOMALIES AND MONEY LAUNDERING: AN ECONOMETRIC ANALYSIS OF ITALIAN MUNICIPALITIES

by Guerino Ardizzi[*], Pierpaolo De Franceschis[**] and Michele Giammatteo***

Abstract

In this study we analyse cash payment anomalies in Italy, at the level of municipality. Cash payments are measured as a share of total payments credited to bank accounts. By estimating an econometric model, we show that the levels of, respectively, income and financial deepening of Italian municipalities are negatively related to the use of cash, as predicted by the theory, whilst the latter is positively affected by the local intensity of criminal activity and money laundering. The analysis allows us to identify the Italian municipalities where the amount of cash transactions is farthest above what is explained by the local socio-economic 'fundamentals'. In these municipalities one can observe the highest share of cash inflows explained by measures of local illegal activities. Based on the results, we provide territorial indicators of the risk associated to anomalous cash handling. From the perspective of a Financial Intelligence Unit, the study has relevant operational implications: risk indicators help target on-site as well as off-site activities on riskiest municipalities. Judicial authorities and law enforcement agencies, too, could benefit in their activities from the geographical distribution of (cash-related) money laundering risk emerging from the methodology developed in this study.

Sommario

Lo studio propone un modello econometrico per identificare le anomalie nell'utilizzo di contante, potenzialmente riconducibili ad attività criminali, a livello comunale; l'analisi riguarda 6.810 comuni italiani nel 2010 (ultimi dati disponibili per alcune fonti esterne). L'utilizzo del contante è misurato dalla quota dei versamenti in contante rispetto al totale dei versamenti a livello comunale: tale variabile, in linea con la letteratura esistente, risulta correlata negativamente con il reddito medio pro-capite e con indicatori di educazione finanziaria e di spessore del settore finanziario; emerge, invece, una correlazione positiva con misure locali di criminalità. Il modello, tenendo conto dei 'fondamentali' socio-economici e finanziari dell'uso del contante, consente di individuare i comuni con la maggiore incidenza di utilizzi anomali: sulla base dei risultati vengono calcolati indicatori comunali di esposizione al rischio di riciclaggio, anche con riferimento a specifiche categorie di reati. Lo studio offre implicazioni operative sia nell'orientare l'azione della UIF e delle altre autorità, sia nel supportare le valutazioni degli intermediari sulla rischiosità della propria attività.

JEL Classification: E26, E42, G28, K42.
Keywords: Money laundering, Crime, Enterprise syndicate, Power syndicate, Regulation.

[*] Bank of Italy, Market and Payment System Oversight Department.
[**] UIF (Italian Financial Intelligence Unit), Bank of Italy, Suspicious Transactions Directorate.
[***] UIF (Italian Financial Intelligence Unit), Bank of Italy, Analysis and Institutional Relations Directorate.

Contents

1. Introduction[1]

A front cover of The Economist famously declared '*the end of the cash era*' already in February 2007, implicitly likening the destiny of paper money to the definitive demise of dinosaurs of ancient times.[2] And indeed the use of cash has been made increasingly cumbersome, inefficient and costly by a host of regulation intensely devoted to limit it and by the widespread diffusion of leaner and more secure intangible means of payment.

Nonetheless, data show that the use of cash has proved far more resilient than the most ferocious and tenacious Tyrannosaurus Rex. For instance, throughout the decade from 2003 to 2013, the value of euro banknotes in circulation worldwide has been rising, admittedly at a decreasing rate, and even showed a significant rebound during the economic downturn of 2008-2009.[3]

In this perspective, Italy is a case of specific relevance for several reasons. Paper money is widely used in the country. In 2009 the value share of cash transactions was 85% with respect to an EU average of 60%,[4] and the dissemination of high-denomination banknotes was second only to Luxembourg within the EU.[5] Tellingly Italy, far from being a Hollywood-style thematic park for long-time extinct pachyderms, is one of the battlegrounds where the war on cash is being waged fiercely. A constraint to the free circulation of cash was introduced since the early 90s and it has been gradually revised downward.[6]

Nonetheless, Italy's preference for paper money is so deep-rooted that even such Draconian measures seem barely to dent it. One of the underlying reasons is believed to lie, among other things, in the particularly large size of the country's underground economy, which the latest official figures pin down at about 17% of total GDP.[7]

Indeed illegal transactions reap all the benefits that cash guarantees, in terms of users' anonymity and source untraceability, which sets it apart from most, if not all, its competitors among modern era means of payment. As a result, the proceeds of many crimes are usually generated as cash, which explains why cash is generally the form that funds of illegal origin take, mostly at the early stages of money laundering.[8] Accordingly, an intensive use of cash is widely held as an effective *proxy* for criminal activities and money laundering.

In this paper we implement an econometric analysis of cash use in Italy, with the aim to distinguish its *illegal* component from the *legal* one.

Under the general framework of the *economics of money laundering* (e.g., Tanzi, 1997; Walker, 1999; Unger, 2007; Masciandaro et al., 2007; Schneider and Windischbauer, 2008; Walker and Unger, 2009; Schneider, 2010) we follow the revised *currency demand approach* proposed in Ardizzi et al. (2014b) and implement a micro-econometric analysis based on municipality-level data. To our knowledge, econometric analysis of this type at such level of geographical detail has not been

[1] The views and the opinions expressed in this paper are those of the authors and do not necessarily represent those of the institutions they are affiliated with. We wish to thank Mario Gara, Domenico J. Marchetti, an anonymous referee and seminar partecipants at UIF, the 2014 SIDE-ISLE Conference in Rome, the 2015 'Shadow Conference' in Exeter and the 2015 SIE Conference in Naples for helpful comments.

[2] See The Economist, 15 February 2007.

[3] http://www.ecb.europa.eu/stats/euro/circulation/html/index.en.html.

[4] Schmiedel et al. (2012).

[5] ECB, 2011.

[6] The threshold has been recently set at € 3,000, after being equal to € 1,000 since April 2012.

[7] Figures are drawn from the National Institute of Statistics and refer to 2008.

[8] See Schneider and Windischbauer (2008) for a description of the three main phases of money laundering: *placement*, *layering*, and *integration*.

attempted so far. Some authors ascribe to (geographically) disaggregated analysis significant benefits, in terms of smaller measurement errors and higher variability of the studied phenomena, with positive implications for the final estimates. Moreover, such level of detail allows us to identify with adequate precision the geographical areas featuring the most significant inconsistencies between cash operations and the local economic background, with important operational bearings (e.g. Mustard, 2010).

We model the demand for "cash deposit" services by using as dependent variable the value of cash inflows into bank accounts normalized to the value of total incoming payments credited to bank accounts. This is consistent with Ardizzi et al. (2014b): it is also our focus to measure the flows of illicit cash accruing to the financial system at the placement stage of money laundering, in which "ill-gotten gains from punishable preactions are infiltrated into a legal bank/economic system; at this junction there is an increased risk of being revealed" (Schneider and Windischbauer, 2008).

Regressors include both socio-economic variables, measuring the size and features of the local legal economy, and crime-related ones, which account for the local illegal environment. In this framework, we can compute the excess demand for cash deposit and identify as more "risky" (or anomalous) those municipalities where cash use is most explained by indicators of criminal activity. That provides an estimate of the risk that "dirty money" is funnelled to the local financial systems – in the shape of cash deposits at banks – in order to be cleaned up.

For our purposes, the estimate of the national size of money laundering (either in absolute terms or relative to GDP) is not of primary interest to us. This objective has been already pursued by several empirical studies for Italy and other EU countries (although they have not led to homogenous results and full agreement on the applied methodologies; e.g. see Zizza (2002) and Ardizzi et al., 2014a). Instead, in what follows we give emphasis to the relationship between the use of cash and criminal activities at the local level, by enriching the knowledge on money laundering-related phenomena through a robust analytical tool for the identification of major territorial anomalies. This objective, among other things, is consistent with the provisions of the Italian law, which states that the analysis of financial flows carried out by the Italian Financial Intelligence Unit has a strategic role in "preventing and combating money laundering through the in-depth examinations of specific anomalies and phenomena involving operators, financial instruments, means of payment, geographical areas and sectors of the economy.[9]"

The study is structured as follows. Section 2 describes the overall conceptual framework and the data; Section 3 presents the benchmark model being estimated and the empirical results; Sections 4 and 5 focus on the construction of *risk indicators* for anomalous cash deposits at local level (these are the sections of the paper more relevant for operational implications for anti-money laundering purposes); Section 6 analyses the relationship between suspicious transaction reports (STRs) and the local use of cash; finally, Section 7 contains some brief concluding remarks and outlines further research developments.

2. Conceptual framework and data

2.1. Conceptual framework

We develop a framework aimed to analyse the relationship between the use of cash and criminal activities in Italy's municipalities, taking into account local economic and financial features.

The use of cash is measured against the use of all other means of payment, so as to

[9] Legislative Decree 231/2007, article no. 6.

account for the relative importance of paper money. Consistently with Ardizzi et al. (2014b), we try to model the demand for cash deposits services, which we proxy by the amount of deposits at credit institutions carried out in cash (as a share of the total amount of deposits).

Thus, our dependent variable ***CASH*** is set equal to the share of cash deposits over total deposits in each municipality:

CASH = *Cash Deposits* / *Total Deposits*

which, by construction, assumes values between 0 and 1.

Again drawing from Ardizzi et al. (2014b), regressors include variables which are meant to capture both the *legal* and *illegal* motivations underlying the use of cash. Hence, our model too includes two groups of explicative variables, relating to, respectively:

- A structural component of the demand for cash deposits services, which captures the legal motivations of cash inflows, linked to, e.g., the structure and the degree of development of the local economy, the functioning of the local financial sector, the benefit from holding money on bank deposits; we also take into account the role played by the shadow economy, including an indicator for the diffusion of irregular (but legal) economic activities, so as to capture that part of cash inflows related to proceeds from tax evasion;
- A 'dirty money' component, which includes indicators of the diffusion of criminal activities and is expected to show positive correlations with that part of cash inflows related to proceeds from illegal activities.

The variables included in the legal (or structural) component of cash demand ($\boldsymbol{X}_L$) consist of: per capita personal taxable income (*YPC*), which can be considered a proxy of local socio-economic development; the total value of electronic payments over the number of bank branches (*ELECT*), measuring the attitude of individuals toward the use of payment instruments other than cash; the per capita number of bank branches (*BCOUNT*), which proxies the level of financial inclusion and deepening. In line with the literature, the expected relation of these variables with the response variable is negative.[10] In fact, all these variables are highly correlated with general education and financial literacy and deepening, leading in general to a lower use of cash and greater confidence in alternative payment instruments (Stix, 2004; Humphrey et al., 1996).

In addition, two dummy variables are introduced so as to take into account geographical-specific factors related to coastal (*COAST*) and mountain (*MOUNT*) municipalities. Coastal municipalities are characterized by non-residents cash-intensive demand for goods and services due to many tourism activities, whereas in mountain municipalities a more difficult access to banking services might imply, on average, greater use of cash.

We do not include the rate of interest in our model. In principle, based on standard economic theory, the interest rate is expected to have a negative effect on the demand for money, via its role of opportunity cost of holding cash in alternative to interest-bearing assets. However, several studies investigating the role of innovative payment systems in cash demand of Italian households (Lippi and Secchi, 2008; Alvarez and Lippi, 2009) point out that the progress in transaction technology may substantially reduce or even eliminate the impact of the interest rate on cash demand. Furthermore, the period covered by our estimations has been characterized by very low interest rates, which is likely to have strongly mitigated the speculative motive (ECB, 2008).

The "dirty money" component of cash demand is proxied by variables concerning two groups of illegal activities ($\boldsymbol{X}_I$), i.e. *enterprise syndicate crimes* (*ENT*) and *power syndicate crimes* (*POW*), a

[10] For a detailed discussion of these supposed correlations see Ardizzi et al. (2014a and 2014b).

distinction which originates from a significant number of studies on criminal economy (e.g. Block, 1980; Asmundo, 2011; Ardizzi et. al., 2014b).

Power syndicate crimes include offenses imposed with the use of violence or strictly associated with the social, economic and military *control* of a geographical area. Following the literature (Ardizzi et. al. 2014b), we proxy them by the local number of detected crimes from extortion (normalized to the resident population) which is the main instrument used by criminal organization to gain control of the local territories.[11]

As to *enterprise syndicate crimes*, they refer to the exchange of illegal goods and services provided on the basis of a mutual agreement between a seller and a buyer, in line with the OECD (2002a) definition of illegal economy. We proxy their relative diffusion in a given municipality by the overall number of detected crimes from drug dealing, prostitution and receiving stolen goods (again, summed up and divided by the resident population).

The distinction between *POW* and *ENT* is crucial for Italy, where organized crime has its "headquarters" predominantly in the Southern regions, while the "retail markets" for illegal goods and services, such as drug and prostitution, are typically more lucrative in the richest Northern districts (Ardizzi et al., 2014a).

These variables are expected to show a positive correlation with the dependent variable, since criminals' enduring preference for anonymous and untraceable cash payments should add to the legal factors underlying the demand for cash, thus increasing the share of paper money payments.

We also use a control variable (***Z***) in order to capture the size of shadow economy. Such variable is the per capita number of building firms (*BUILD*) operating in each municipality. The larger the employment in construction, the higher is potentially the number of irregular workers and the demand for cash deposits due to shadow economy proceeds, *ceteris paribus* (e.g., Torgler and Schneider, 2009; Capasso and Jappelli, 2013). Hence, *BUILD* should be a good proxy for evasion of tax and social contributions, thus helping us to distinguish cash proceeds coming from the underground economy from those originating from fully-fledged criminal activities.

2.2. Data

The main database used in this study is that of the Aggregate Anti-Money Laundering Reports (SARA from the Italian acronym). Under the Italian anti-money laundering law (Legislative Decree no. 231/2007), banks and other financial intermediaries record all transactions amounting to over 15,000 euros in a specific archive (Single Electronic Archive); they are required to aggregate individual records according to several criteria and then file the resulting reports on a monthly basis to Italy's Financial Intelligence Unit (UIF).[12]

In 2013, UIF received over 100 million aggregate records, corresponding to about 315 million individual transactions worth nearly 21 trillion euro. About 95% of total aggregate records were received by banks; other reporting entities include fiduciary and asset management companies, securities firms and insurers accounting for the residual share.

---

[11] 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 "whether one wants or not, one gets it and is required to pay for it." Similar arguments may apply to 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 Apulia.

[12] Aggregation criteria include, for example, the type of transaction, the intermediary's branch where the transaction took place, the client's residence (at municipality level) and his/her economic sector. Each aggregate record includes information on the total amount transacted, the corresponding cash component and the number of underlying individual transactions being aggregated.

The data used in the regressions refer to 2010 as the most recent year for which all needed information was available at the time of the analysis[13]. We consider the transactions recorded by banks at municipality level, distinguishing between cash and other instruments of payments (cheques and wire transfers). In particular, the SARA data has been used to build the dependent variable of the econometric model ($CASH_i$, where i identifies the municipality), but also two regressors, i.e. the total value of electronic payments and the per capita number of bank branches.

With regard to the variables accounting for the socio-economic background, the data on local personal taxable income were acquired from the Italian Revenue Agency ("Agenzia delle Entrate") website. Municipalities' resident population (which is used to normalize most variables) and the two dummies identifying coastal and mountain municipalities were extracted from the website of the National Institute of Statistics, while the number of building firms operating in each municipality was taken from the central registry of commercial businesses (Infocamere).

Data on local crime rates were obtained from a confidential dataset held by police forces ("Sistema d'Indagine", SDI). It supplements the information from victim reports with that on criminal events directly collected by police departments. The main advantage deriving from its use lies in that, being its data gathered for investigation purposes, the timing of documentation should reflect the true timing of the offence.

Table 1 includes the complete set of variables used in the paper and shows some key summary statistics.

Table 1
List of variables and summary statistics

Variable	mean	median	sd
Cash inflows (€ million)	*32.90*	*5.70*	*263*
Total inflows (€ million)	*1,090*	*34.70*	*32,900*
$CASH_i$	0.28	0.19	0.25
YPC_i (€)	10,420	10,808	3,137
$ELECT_i$ (€ 1,000)	17,705	6,607	53,119
$BCOUNT_i$ (x 10,000)	17.00	12.90	14.00
$COAST_i$	0.09	0.00	0.29
$MOUNT_i$	0.49	0.00	0.50
ENT_i (x 1,000)	1.14	0.75	3.20
POW_i (x 1,000)	0.14	0.00	0.31
$BUILD_i$ (x 1,000)	4.68	4.36	2.72

Source: authors' own calculations.

Unfortunately, the complete set of explanatory variables is not available for all the 8,094 Italian municipalities in the year of reference;[14] therefore, the final sample considered for the

[13] Another advantage of using 2010 as benchmark year is that, if we had focused on more recent years, the effect of both significant changes on the ceiling on cash transactions and the almost unprecedented economic crisis could have potentially impaired a clear reading of the results. The only exception to the use of 2010 data is local crimes statistics (see below), for which the latest data available referred to 2009; for robustness purposes, given the high variability of the data at municipality level, we used the sum of crimes detected in the period 2008-2009.

[14] Italian demographic statistics are available at http://www.istat.it/it/files/2011/06/italiaincifre2011.pdf.

econometric analysis contains 6,810 observations (which shrink further when more variables and transformations are included in additional specifications of the model).

3. Structural model and estimation results

3.1. The econometric model

Assuming a linear relation between ***CASH***, $\boldsymbol{X}=(\boldsymbol{X}_L, \boldsymbol{X}_I)$ and $\mathbf{Z}$, we first apply a simple linear regression model (OLS) to estimate the following equation:

$$CASH_i = \alpha + \sum_k \beta_{ki}\boldsymbol{X}_i + \sum_h \beta_{hi}\boldsymbol{Z}_i + \varepsilon_i \qquad [1]$$

where the error term ε_i is uncorrelated with the regressor vectors $\boldsymbol{X}$ and $\boldsymbol{Z}$.

As documented by the OLS diagnostic tests shown in the Appendix, results show that the homoscedasticity and normality assumptions are violated, even after introducing logarithmic and quadratic transformations of our variables.

More importantly, since the observed values of our dependent variable fall between 0 and 1 by construction, it would be reasonable to obtain predicted values also falling in the same interval.[15] This requirement is accomplished by extending the previous model [1] to a special class of Generalized Linear Model (GLM), generally defined as:

$$g\big(E(y/\boldsymbol{X})\big) = \boldsymbol{X}\beta, \qquad y \sim F$$

where y represents the fractional response variable, $\boldsymbol{X}$ is the vector of all explanatory variables, $g(\cdot)$ a monotonic function (*link-function*), and F belongs to the exponential family. Assuming in our model that the response variable y follows a *binomial* distribution[16] and $g(\cdot)$ is the *logit* function we obtain:

$$logit[E(y_i/\boldsymbol{X})] = \alpha + \sum_k \beta_{ki}\boldsymbol{X}_i + \sum_h \beta_{hi}\boldsymbol{Z}_i + \varepsilon_i \qquad [2]$$

In particular, we estimate a *fractional logit model* developed by Papke and Wooldridge (1996), whose (conditional) predicted values are given by

$$E(y/\boldsymbol{X}) = \frac{\exp(\boldsymbol{X}\beta)}{1+\exp(\boldsymbol{X}\beta)} \qquad [3]$$

and are defined for each sample realization $\boldsymbol{X} = (\boldsymbol{x}_1, \ldots, \boldsymbol{x}_k)$, where k is the number of predictors used.

Furthermore, we adopt log transformation of those variables which present a strongly skewed distribution and remove the assumption of linearity in the crime parameters by adding quadratic terms in the 'dirty money' component in order to allow for non-linearities.

3.2. Estimation results

Table 2 presents the coefficient estimates and marginal effects obtained by the implementation of the GLM model [2].

The estimates highlight a negative and significant correlation between cash inflows and the structural variables: higher values of per capita income, electronic payments, and per capita number of bank branches are negatively correlated with the relative use of cash. As anticipated in the previous sections, this is consistent with the existing literature, for which higher general education and financial literacy, being positively correlated with individual incomes and confidence

[15] See Figure A2 in the Appendix for a graphical comparison between estimated and observed values of the dependent variable in case of OLS and GLM methods.

[16] Potential model specification problems can be prevented by calculating robust standard errors.

in alternative payment instruments, lead to a lower use of cash (Stix, 2004; Humphrey et al., 1996). Also, the use of cash is confirmed to be more intense in municipalities located in coastal or mountainous areas.

Table 2
GLM Estimates and Marginal effects

Regressors	Coef.	*Robust S.E.*	dy/ex[a,b]	*Delta-method S.E.*	*95% C. I.*	
					Low.	*Upp.*
Ln(YPC)	-0.483***	*0.026*	-0.645***	*0.034*	*-0.712*	*-0.579*
Ln(ELECT)	-0.596***	*0.005*	-0.687***	*0.005*	*-0.696*	*-0.677*
Ln(BCOUNT)	-0.548***	*0.015*	-0.208***	*0.005*	*-0.218*	*-0.197*
COAST[b]	0.353***	*0.021*	0.059***	*0.004*	*0.051*	*0.067*
MOUNT[b]	0.147***	*0.014*	0.025***	*0.002*	*0.020*	*0.030*
ENT	0.025***	*0.005*	0.004***	*0.001*	*0.002*	*0.005*
ENT^2	-0.001***	*0.001*				
POW	0.177***	*0.042*	0.002***	*0.001*	*0.001*	*0.003*
POW^2	-0.068***	*0.020*				
Ln(BUILD)	0.068***	*0.012*	0.013***	*0.002*	*0.009*	*0.018*
CONS	9.360***	*0.208*				
AIC = 0.648; *Deviance = 256.9*; *Obs. = 6,576*						

GLM: *Variance function*: Binomial; *Link function*: Logit.
*** p<0.01, ** p<0.05, * p<0.1.
[a] Semielasticities: percentage point variation in dependent variable for 1% variation of each independent variable. Conditional marginal effects (Average Marginal Effects - AME).
[b] dy/dx for dummy variables (discrete changes from the base level).
Source: authors' own calculations.

Likewise, the signs of the coefficients for the crime variables show a positive relationship with the use of cash, as expected. Moreover, the signs of the quadratic terms suggest a decreasing marginal effect for *power* and *enterprise*.

Lastly, the results are consistent with the intuition about the relevance of the shadow economy: the relative use of cash is larger in municipalities with a higher per capita number of building firms.[17]

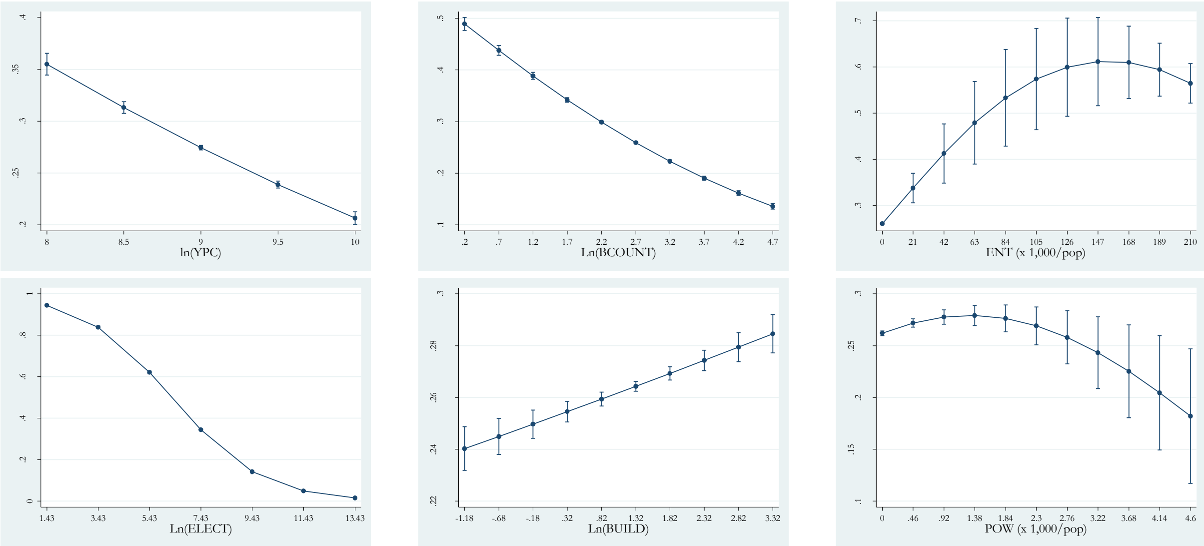
The marginal effects (dy/ex) of Table 2 measure the average variation in the response variable for a 1% increase of each regressor (corresponding to the average of conditional marginal effects). For example, the impact of *enterprise crimes* is estimated to be 0.004 on average, that is a 1% increase of crimes is associated, on average, with a rise of 0.4 percentage points in the share of cash inflows, which corresponds to approximately 4 million euro (for power crimes, the corresponding figures are 0.2 percentage points and 1.6 million euro). The slightly larger marginal effect of the *enterprise* variable with respect to *power* mostly reflects the main function the two different groups of criminal conducts serve. While *power* illegal activities aim at gaining control of

[17] As to robustness, the GLM results are consistent with the OLS estimates shown in the Appendix. Note that, with respect to the OLS approach, the GLM estimation method allows us to obtain more accurate fitted values of relative cash inflows. More in detail, the OLS estimates of Table A1 show that the model fit is greatly improved as a result of the log transformation of the variables included in the structural component and the quadratic term of the crime variables, which ensures a marked increase in the R-squared value (from 0.30 to 0.84). Moreover, as the Figure A2 shows, the GLM fitted values of the dependent variable are linearly related to the observed ones, as the logit fractional model predicts.

an area with the objective of establishing criminal influence on its economic and socio-political environment, *enterprise* offences pursue highly lucrative sources of income usually involving a larger number of people and profit opportunities.

Differently from standard linear models, the GLM model that we estimated provides predicted values which vary with each sample realization of the explanatory variables. In order to better appreciate the estimated marginal effects, Figure 1 shows the relationship between the expected value of the response variable and each predictor along the entire range of their observed values.

Figure 1
Marginal effects of continuous predictors



AME conditional marginal effects with 95% CIs

Per capita income and per capita number of building undertakings are shown to have a nearly linear relationship with cash deposits. The negative correlation between the latter and the value of electronic payments is steepest at intermediate values thereof and flattens at both tails. As for the crime variables, we observe quite different marginal behaviours. Notably, while in the case of *power* the positive correlation with the dependent variable soon decreases (with the marginal effect turning negative), for *enterprise* it is strongly increasing for a wide range of crime rates. This should come at no surprise. In fact, it is reasonable to speculate that the control exerted by criminal organisations in specific territories through coercion and violence (as measured by *POW*) tends to quickly 'saturate' the socio-economic context (with decreasing gains associated to additional illegal actions). Conversely, the anomalous use of cash related to *enterprise* crimes increases with the corresponding expansion of illicit markets (e.g. drug trade).

4. Indicators of anomaly

One of the main objectives of this study is to define a set of *risk indicators* for anomalous cash deposits at local level, as derived by our estimated model.

Beyond the contribution to the literature and to the general knowledge of the phenomenon of interest, such an indicator would have significant operational implications. Indeed, it might provide the authorities involved in the national anti-money laundering (AML) system with an additional effective tool to discharge some of their tasks. One example can help clarify this point. FATF's Recommendation no. 1 requires that countries perform a national assessment of the risk of money laundering and terrorism financing (NRA) so as to design proportional AML measures and re-allocate resources in the most effective way. An indicator of risk based on anomalous cash deposits could certainly be most valuable in this perspective.[18]

Consistently with the literature on *currency demand approach* (Tanzi, 1980) and with the extensions proposed by Ardizzi et al. (2014b) we compute, for each municipality, the "excess cash inflows" — i.e., the portion of cash inflows which is explained by the illegal component — as the difference between the fitted values of *CASH* obtained from the full model [2] and the predicted values obtained from a restricted version of the same equation where the coefficients of *ENT* and *POW* are alternatively set equal to zero, while the coefficients of all other regressors are the same as those estimated with the full model.[19] That is, for each municipality *i*, our measure of "excess cash inflows" is $\hat{y}_i - \hat{y}_{i,c(o)}$, where $\hat{y}_i$ is the fitted value of the full model [2], and $\hat{y}_{i,c(o)}$ is the value predicted by the same estimated model after setting, alternatively, *ENT*=0 or *POW*=0.[20] Such measures are computed separately for the *enterprise* and *power* types of criminal activities, with the aim of highlighting potential different effects between geographical areas.[21] Each measure $\hat{y}_i - \hat{y}_{i,c(o)}$ is the share of cash inflows explained (or predicted) by criminal activities. As such, it can be taken as a model-based measure of the risk that an individual cash deposit, in a given municipality, is somehow generated by some criminal activity.

We then derive provincial measures of the risk associated to anomalous cash inflows. A first index is given by the simple (unweighted) mean of the "excess cash inflows", that is:

$$\overline{excash_j} = \frac{1}{n_j}\sum_{i=1}^{n_j}\left[\hat{y}_i - \hat{y}_{i,c(o)}\right] \quad [4]$$

where n_j is the number of municipalities in the province of analysis *j*. The index [4] can be then taken as a measure of the *relative risk* of cash-related money laundering in the province *j*, that is the average risk that an individual cash deposit in a given province is correlated to some criminal activity.

While being potentially quite useful, such index doesn't convey *per se* any information on the absolute value or order of magnitude of the excess cash inflows involved. For example, a tiny or scarcely populated province heavily infiltrated by criminal organizations may have a high *relative risk* of money laundering, but — because of its limited economic size — the order of magnitude of the flows involved may be quite modest. On the other hand, a major province may have a low incidence of 'excess' cash, but — because of its economic relevance — the corresponding absolute unexplained flows may be very large.

In order to obtain a provincial indicator of the *absolute risk* of money laundering in the sense just mentioned, we propose also a second index, which is a weighted mean of the "excess cash inflows":

$$\overline{excash_{j,w}} = \sum_{i=1}^{n_j} w_i\left[\hat{y}_i - \hat{y}_{i,c(o)}\right] \quad [5]$$

where w_i is the ratio between the value of cash *inflows* annually carried out in the municipality *i* and the total amount at national level. This second index thus attaches greater weight to (model-based) crime-related cash deposits in areas featuring a higher national share of cash payments.

Clearly the two indicators are both valuable for the purpose of identifying risk, although

---

[18] Indeed, the results of earlier versions of this work have been incorporated in Italy's NRA for 2014.

[19] When the specification of the model involve the quadratic transformation of these variables, also their coefficients are simultaneously set equal to zero.

[20] Note that, while in a linear model the "excess cash inflow" simply corresponds to the product of a crime variable and its regression coefficient, in the case of GLM models it corresponds to the product of a crime variable and its varying marginal effect (which is municipality-specific, in our case).

[21] Such a distinction is crucial in Italy, where organized crime operates predominantly in the South, while illegal traffics are mostly exported in the richest Regions of the Centre-North, where retail markets of illicit goods (e.g. drug) are more profitable.

they may be so within quite different scopes of activity. For instance, from the viewpoint of those intermediaries and other reporting entities required to file suspicious transaction reports (STRs) under AML regulation, a measure of unweighted (relative) risk may be more helpful to the end of detecting flows of funds of illegal origin irrespective of their size, since it conveys information on the probability that an observed cash inflow in a specific area may have actually originated from a criminal activity. Conversely, law enforcing agencies may be keener to concentrate their resources and investigative efforts on those municipalities where cash flows of likely illegal nature are heftier and more sizable, as measured by the weighted (absolute) risk indicator.

It is worth stressing that the results one index yields may differ quite significantly from those produced by the other with reference to both classes of crimes. That is an obvious implication of how the indicators are built: clearly when ranking provinces on the basis of the absolute magnitude of the excess flows, the wealthier districts tend to rank higher due to their sizable amount of cash in circulation in absolute terms, though their relative share of cash deposits explained by the criminal component (as measured by the unweighted index) may be relatively low.

The results on the provincial distribution of the 'excess cash inflows' explained by *power crimes* are reported in the maps of Figure 2, for both the unweighted and weighted indexes (respectively, the risk indicators [4] and [5] defined above). Each province is given a certain level of risk based on the corresponding quartile of the distribution of the indicator. While both indicators (unweighted and weighted) provide interesting insights, for the category of *power crimes* we tend to focus on the unweighted index. The rationale is that criminal organisations engage in *power-style* illegal activities in an area with the goal of establishing and reinforcing their grip on that area, which may eventually (but not necessarily) lead to immediate economic gains, but are expected to produce results also over time and at other levels (for instance, by allowing control over local political institutions). A good measure of this 'grip' seems to be exactly the share of the cash circulating that can be associated to this type of crimes. Turning to the results, the provinces with higher risk of use of cash related to *power crimes* are mainly concentrated in the South, as one may have expected, given how powerful "mafia-style" criminal organisations have grown to be in those areas. Such result is not affected to a significant degree by the type of index (whether weighted or not) one refers to. Conversely, few relevant anomalies located in major cities of the Centre-North emerge more clearly from the weighted index, which attaches greater weight to provinces with larger absolute values of cash inflows, as already emphasized.

The cash anomalies associated to *enterprise crimes* are described in Figure 3. With regard to this category of criminal activities, we look preferably at the weighted index, based on *absolute* flows, because the driver of such activities is the size of the market for illegal goods and services, proxied by the absolute magnitude of the cash circulating in such market estimated by the model. Referring to the weighted indicator (right-hand side of the diagram), a wide area with high risk levels emerges in the North. Such area includes some highly populated metropolitan areas, such as Milan, Genoa, Venice and Florence, where the order of magnitude of the flows involved is significant. It also includes few rich provinces (nearly unaffected by the unweighted index) which rank high in the anomaly chart, due to the size of their economy and the respective cash flows. As to the South, high levels of risk are reported in largely populated areas (e.g., Naples, Bari, Palermo and Catania); other provinces are 'downgraded' in terms of the *absolute risk* of cash-related money laundering – in spite of the pervasive mafia infiltration – because of the smaller size of the respective money flows.

Figure 2
Provincial unweighted and weighted mean of cash anomalies due to *power crimes*

Unweighted *Weighted*

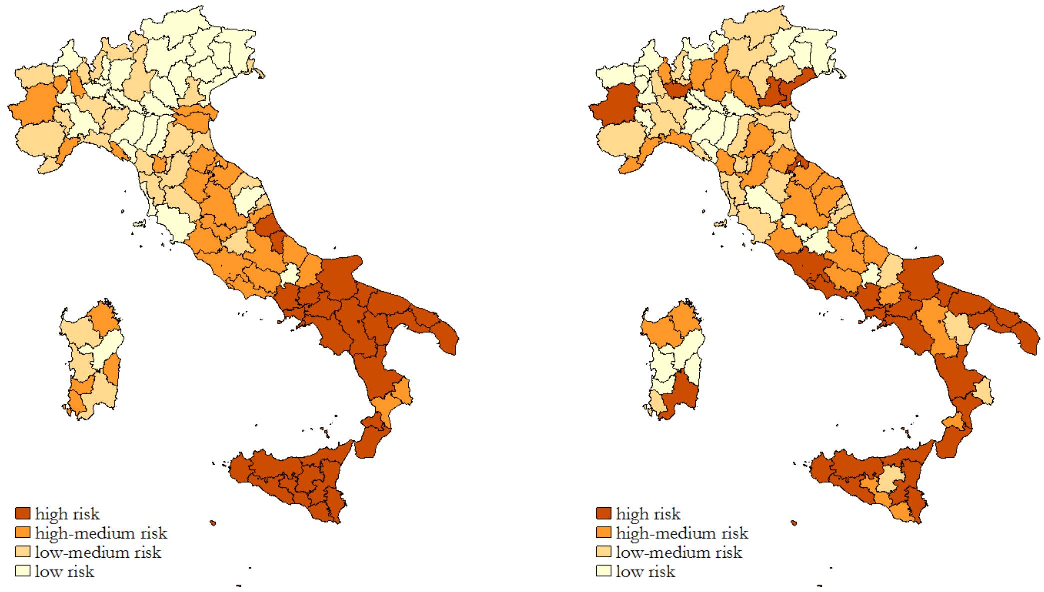
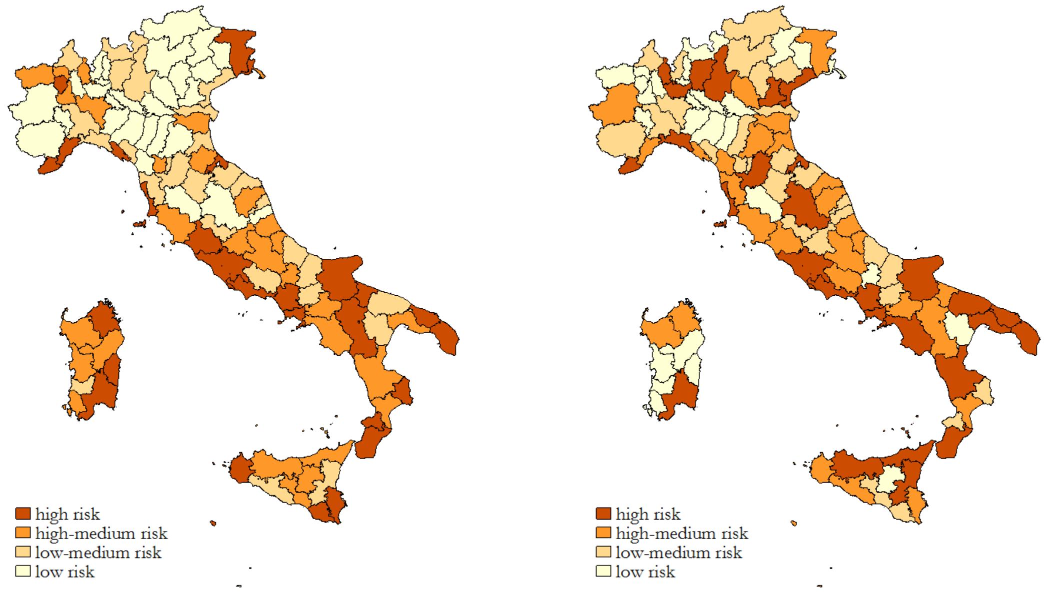


Figure 3
Provincial unweighted and weighted mean of cash anomalies due to *enterprise crimes*

Unweighted *Weighted*

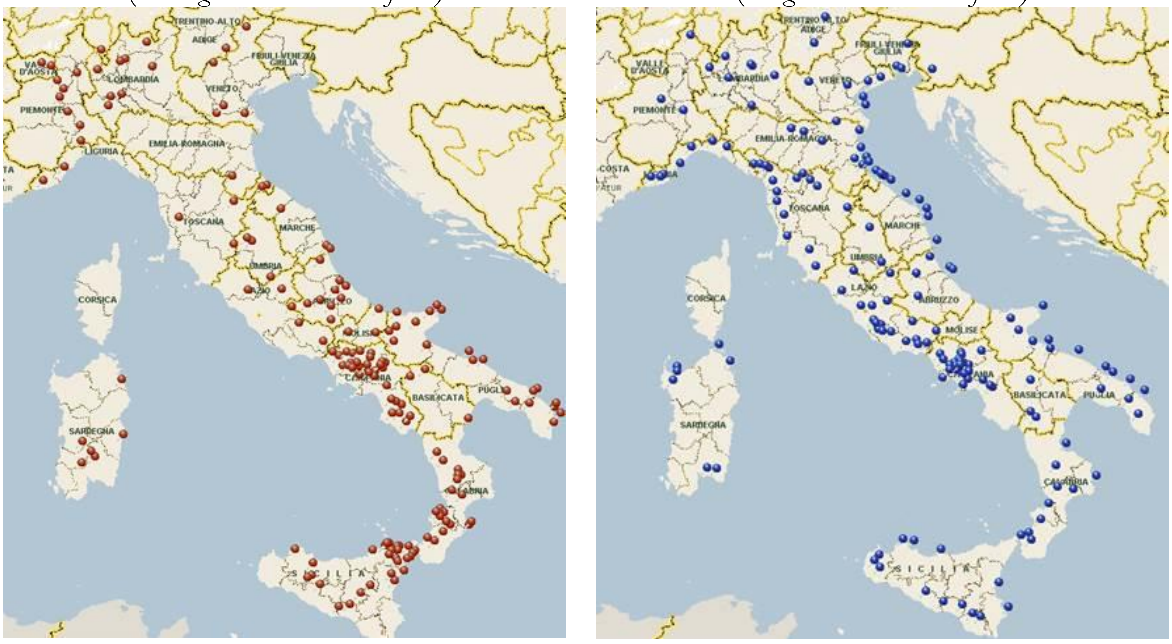


While the provincial aggregation of "excess cash inflows" — defined in equations [4] and [5] and shown in Figures 2 and 3 — is a convenient tool to illustrate the geographical distribution of the anomaly indicator and single out the riskier provinces, the most accurate identification of anomalies is of course that at the municipality level, provided by the model-based, individual measures of "excess cash inflows" $\hat{y}_i - \hat{y}_{i,c(o)}$. Furthermore, the results at the municipality level are not only the most accurate, but also the most relevant from the operational perspective of anti-money laundering authorities. In fact, the municipalities featuring the larger share of cash flows explained by crime variables can be used as a benchmark for further financial investigations, taking into account that the SARA database can be drilled down to the level of bank branches. From the financial oversight viewpoint, for instance, such information could be used in order to target for on-site audits those banking institutions with the most anomalous cash flows.

To this end we simply rank the municipalities on the basis of the size of "excess cash inflows"; Figure 4 shows the most anomalous municipalities, i.e. those belonging to the top 2.5% tail of the distribution of "excess cash inflows", for, respectively, *power* and *enterprise crimes*. As argued before, for the *enterprise crimes* we report the results for the weighted cash inflows.

Figure 4
Anomalous municipalities
(Top 2.5% of the distribution)

POWER crimes (*Unweighted excess cash inflows*) — ENTERPRISE crimes (*Weighted excess cash inflows*)



With regard to cash anomalies related to *power crimes*, the way the riskiest municipalities are distributed across the national territory highlights how the extent to which organised crime controls and infiltrates the local economic environment is more widespread and endemic in the South (with several cases also emerging in some North-Western and Central municipalities). On the other hand, quite symmetrically, the market for illicit goods and services, as those associated to the *enterprise crime* variables, is sizable not only across the wealthy Northern districts of the country, but also in several Southern municipalities (most notably around Naples).

5. An alternative indicator of anomaly based on estimation residuals

By including local indicators of crimes among the explanatory variables for the level of cash use at municipality level, the model presented in the previous sections implicitly assumes that the proceeds of any type of criminal conducts performed in a given area are laundered locally, thus contributing to the flow of cash observed in the same area. Since financial flows are certainly mobile within the territory of a single country, one can relax the assumption of a strict relationship between the amount of crimes committed in one area and the amount of money to be locally laundered.

To this end, by following the rational of the approach proposed by Cassetta et al. (2014) in their investigation of anomalous off-shore wire transfers, we estimated the model *without* the indicators of criminality, and focused on the estimation residual, which represents the component of the dependent variable (i.e. the share of cash on total deposits) which is *unexplained by economic fundamentals* and other structural, 'physiological' determinants of cash use.

With respect to the former method described in the previous sections, the latter indicator has the advantages and disadvantages of not being 'anchored' to the number of crimes reported locally: the advantage is that the new indicator may potentially capture criminality-related use of cash which is not proportional to criminal records; the disadvantage is that it contains more noise, i.e. includes information on other components of the dynamics of the dependent variable which are unrelated to crime, including the erratic component.

The outcome of the GLM estimation of the model without indicators of crime are reported in Table 3. The substance of the results largely confirms that shown in Table 2 in terms of both the sign and the statistical significance of all the estimated coefficients, while slight differences arise only in the absolute size of the coefficients themselves.

Table 3
GLM Estimates of the model without indicators of crime

Regressors	**Coef.**	***Robust S.E.***
Ln(YPC)	-0.495***	*0.025*
Ln(ELECT)	-0.593***	*0.005*
Ln(BCOUNT)	-0.556***	*0.015*
COAST	0.385***	*0.021*
MOUNT	0.141***	*0.014*
Ln(BUILD)	0.073***	*0.012*
CONS	9.512***	*0.204*
AIC = 0.6469; *Deviance = 260.2*; *Obs. = 6,576*		

GLM: *Variance function*: Binomial; *Link function*: Logit.
*** p<0.01, ** p<0.05, * p<0.1.
Source: authors' own calculations.

The indicator of anomaly, as already emphasized, is the estimation residual; more specifically, consistently with the literature on outlier detection, we considered anomalous the municipalities corresponding to the 2.5% largest studentized Pearson residuals.[22] The map of such municipalities is shown in Figure 5.

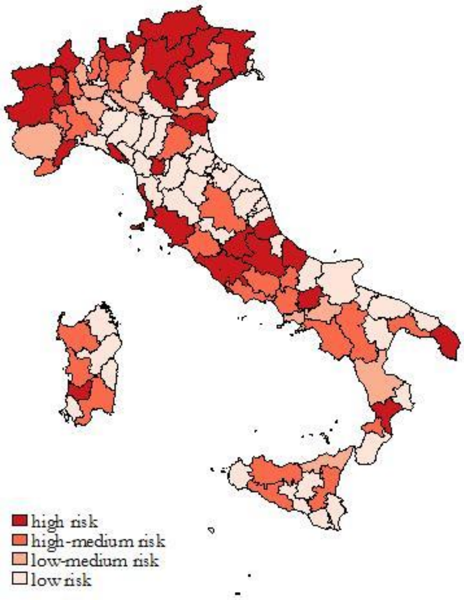
With respect to the maps shown in Figure 4 in the previous section, anomalous municipalities appear now more evenly distributed across the country. In a way, the new map of local outliers depicted in Figure 5 seems a blend of the two previous maps (each of which corresponding to one type of crimes). However, the most noticeable difference with previous maps is that the new approach delivers a much higher number of anomalous municipalites located in the North (65% of all outliers, compared to 4% in the *power crimes* indicator and 22% in the *enterprise crimes* one). This seems consistent with the rational behind the new indicator: after releasing the working hypothesis that the proceeds of crimes are laundered (only) locally, not surprisingly the municipalities which seem to attract more money to be laundered through cash are located in the wealthy North.

[22] Studentized residuals are considered in order to take into account as much as possible the effects of scale.

Figure 5
Anomalous municipalities
(Top 2.5% of the distribution)

The results of the new indicator of anomaly can be aggregated at provincial level; in order to do so we considered, for each province, the share of municipalities which are identified as outliers on the total number of municipalities located within a given province[23]. The results are shown in Figure 6.

Figure 6
Provincial incidence of anomalous municipalities
(based on top 2.5% of the municipality distribution)



[23] Notice that this aggregation criterion is quite different from that used for the previous indicator of anomaly. Our choice reflects the arguably different nature of the two indicators. In the case of the earlier indicator, its size has a clear economic interpretation (namely, in terms of a quantitative measure of 'excess cash flows') and, therefore, it seemed appropriate to take a (provincial) average of it (either weighted or unweighted, according to the case). Conversely, the new indicator is an estimation residual, and as such its size does not have a clear economic interpretation as a measure of some factor or phenomenon. Accordingly, our provincial aggregates are based on a statistical criterion and are independent of the size of individual residuals.

Consistently with what we already observed at municipality level, the anomalies captured by the new indicator are much more concentrated in the North compared to the maps presented in Figures 2 and 3 (regardless of the type of crimes considered in the corresponding indicators). The presence of anomalies in Central Italy seems generally similar in scope to that depicted in previous maps, whilst the incidence of outliers in Southern provinces, with few exceptions, is clearly lower. What could explain this north-bound shift of cash balances unexplained by economic fundamentals? As previously argued, the anomaly-detection methodology applied here severes by construction the geographical tie between locally observed levels of cash use and the intensity of *local* criminal activities. Since Italy's Northern regions are among the most wealthy in the country, criminals may be driven to transfer their outstanding cash balances to the North from elsewhere in the country, so as to exploit the more enticing investment opportunities offered there[24].

6. 'Excess' cash inflows and suspicious transaction reports (STRs)

In this section we expand the model described in the previous sections so as to offer a first econometric investigation of the relationship between cash inflows and the suspicious transaction reports (STRs) received by Italy's FIU.[25] For the very reason why cash is held as a proxy for the size of the criminal economy (its intrinsic characteristics of anonymity and lack of traceability), intensive use of cash is typically used by banks and other reporting intermediaries under AML/CTF regulation as a main indicator of potential funds of illegal origin. Not surprisingly, therefore, unusually large or frequent cash deposits tend to 'generate' an *ad hoc* category of suspicious transaction reports: indeed, cash transactions are among the most common financial conducts featured in STRs (especially those received by the UIF, given the extremely low threshold on the use of cash enforced in Italy which makes very large cash deposits all the more unusual). Beyond this nexus between cash inflows and cash-based STRs, which is quite obvious, it may be interesting to explore, more in general, the relationship between cash inflows and STRs at large.

As a first step, we included in the benchmark model the number of STRs filed to the UIF in 2010 from each municipality. In particular, not all STRs have been included among regressors, but only high-risk STRs (*STR*) and those reporting anomalous transactions involving the use of cash (*STRCASH*), both normalized to population.[26] Results are reported in the first column of Table 4.

---

[24] In principle, another possible explanation is that the higher concentration of anomalies in the North produced by the new approach may reflect, at least to some extent, the larger shadow economy, the analysis of which lies outside the scope of our investigation. In fact the new approach, by relaxing the connection between the amount of cash to be laundered and the number of reported crimes, may captures not only cash balances potentially linked to the illegal economy, but also those linked to the shadow economy (at least to the extent that the BUILD regressor, included to control for it, falls short of fully accounting for such component).

[25] Under the Italian anti-money laundering law (Legislative Decree no. 231/2007) reporting intermediaries are required to "*send a report of any suspicious transactions to the FIU whenever they know, suspect or have reason to suspect that money laundering or terrorist financing is being or has been carried out or attempted. The suspicion may arise from the characteristics, size or nature of the transaction or from any other circumstance ascertained as a result of the functions carried out, also taking account of the economic capacity and the activity engaged in by the person in question, on the basis of information available to the reporters, acquired in the course of their work or following the acceptance of an assignment*." (art. 41).

[26] Each STR has been rated according to authors' calculations which take into account the typology of the anomalous financial conducts being reported and whether any investigative activity originated from the STR. Since May 2011, the UIF's electronic platform for processing STRs embeds an algorithm computing automatically each report's level of risk, based on several factors, such as the amount of funds involved and the connection with previous cases or ongoing investigations. The risk-mark each report is given as a result of this automatic assessment process can be subsequently adjusted according to what emerges from the investigations conducted by UIF financial analysts.

Table 4
GLM Estimates

Regressors	(1) Coef.	(1) *Robust S.E.*	(2) Coef.	(2) *Robust S.E.*	(3) Coef.	(3) *Robust S.E.*
Ln(YPC)	-0.484***	*0.026*	-0.490***	*0.026*	-0.494***	*0.025*
Ln(ELECT)	-0.599***	*0.005*	-0.610***	*0.005*	-0.612***	*0.005*
Ln(BCOUNT)	-0.551***	*0.015*	-0.538***	*0.015*	-0.536***	*0.015*
COAST	0.352***	*0.021*	0.343***	*0.021*	0.340***	*0.021*
MOUNT	0.149***	*0.014*	0.152***	*0.014*	0.153***	*0.014*
ENT	0.025***	*0.005*	0.022***	*0.005*	0.023***	*0.005*
ENT^2	-0.001***	*0.001*	-0.001***	*0.001*	-0.001***	*0.001*
POW	0.175***	*0.041*	0.164***	*0.041*	0.160***	*0.041*
POW^2	-0.068***	*0.020*	-0.065***	*0.020*	-0.061***	*0.019*
Ln(BUILD)	0.068***	*0.012*	0.061***	*0.012*	0.059***	*0.012*
STR	0.005	*0.005*	-0.011	*0.007*	0.001	*0.006*
STRCASH	0.069***	*0.021*	0.039**	*0.019*	0.011	*0.019*
RISK			0.072***	*0.008*	0.167***	*0.021*
RISK^2					-0.040***	*0.008*
CONS	9.395***	*0.208*	9.479***	*0.209*	9.520***	*0.209*
	AIC = 0.648; *Deviance = 256.2*; *Obs. = 6,576*		*AIC = 0.648*; *Deviance = 253.7*; *Obs. = 6,576*		*AIC = 0.648*; *Deviance = 253.0*; *Obs. = 6,576*	

GLM: *Variance function*: Binomial; *Link function*: Logit.
*** p<0.01, ** p<0.05, * p<0.1.
Source: authors' own calculations.

A positive and strong correlation emerges with cash-related STRs, as largely anticipated, while general purpose high-risk STRs do not appear to be correlated with cash inflows. The coefficient estimate of *STR*, however, may be affected by the extremely large number of zeros in the domain of the variable (about 90% of the municipalities). As a further step, therefore, we added to the regressors a measure of the average riskiness of STRs at municipal level (*RISK*, obtained as municipal average of the risk of each individual STR), both as a linear and quadratic term. While *RISK* is also a good measure of the risk intensiveness of the flow of STRs filed in a given municipality, unlike *STRs* it is not a zero-inflated variable, and takes not-zero values in all municipalities.

The results are quite interesting. The coefficient estimate of *RISK* is positive and highly significant, showing that the amount of cash inflows in a given municipality is positively correlated, *ceteris paribus*, with the relevance of the local money laundering activity, as proxied by the average riskiness of the local STRs. This is a further confirmation of the pivotal role played by cash in the money laundering process, and of the usefulness of cash-based indicators such as those developed in this study. On the other hand, the negative and highly significant coefficient estimate of the quadratic *RISK* term suggests a decreasing marginal effect: a more intensive use of cash in a municipality is associated to higher STRs riskiness, but only up to a certain threshold (see also Figure A3 in the Appendix); this is fully consistent with the experience of UIF's STRs analysts, whereby cash is relatively uncommon as a means of money laundering in high-profile cases.

Summing up, the simple analysis of STR data reported in this section has confirmed the important role and relevance of cash inflows as an indicator of money laundering activity, as proxied by STR riskiness. On the other hand, the strong link weakens as the 'riskiness' (relevance) of the anomalous financial conduct rises. In other words, the effectiveness of cash as a 'red flag' for money laundering wanes in connection with more complex money laundering schemes, as is also suggested by STRs analysis.

7. Concluding remarks

On the face of figures measuring nation-wide diffusion of paper money — which make Italy one of the EU countries with the highest incidence of cash use — the era of cash ultimate demise does not seem to have come yet, since widespread use of alternative, more efficient, means of payment and increasingly coercive law-based constraints to the use of paper money have not yet produced the same disruptive consequences as the asteroid hitting the earth did for dinosaurs.

Beside cultural, social and economic factors, the number of cash transactions performed at the country's financial intermediaries is believed to be significantly affected by the amount of proceeds annually generated by criminal activities in the country, due to the extensive infiltration of the economy by organised crime. As a direct consequence, the study of the relationship between the use of cash and the level of criminal activity in a given territory may provide interesting insights on money laundering-related phenomena.

In this paper we have addressed this research topic by adapting the revised currency demand approach proposed by Ardizzi et al. (2014a and 2014b) and implementing an analysis of data at municipality level, drawing extensively on the highly-detailed SARA database of the Italian FIU. The final goal has been to pin down – on the basis of an econometric model – the "illegal motivation" underlying the anomalous use of cash and identify accordingly the most anomalous Italian municipalities, meaning by this those with the largest inconsistencies between the amount of cash payments and the local economic 'fundamentals'.

In line with the literature, we found a negative and significant correlation between cash inflows and per capita income, the value of electronic payments, and the per capita number of bank branches observed in each municipality. Indeed, individual incomes as well as confidence in alternative payment instruments, being positively correlated with higher general education and financial literacy, lead to a lower use of cash. On the other hand, the indicators of criminal activity have been found to be positively correlated with the use of cash. In particular, by distinguishing between illegal activities characterised by "market" transactions (*enterprise crimes*) and those aimed at ensuring a tighter control of the territory (*power crimes*), we estimated that each 1% increase of related crimes corresponds to an average impact of, respectively, 0.4 and 0.2 percentage points on relative cash inflows (which, in turn, correspond to about 4 and 2 million euro of cash payments).

As a step further, we built an indicator of anomaly based on the estimation results. In particular, such indicator has been computed, for each municipality, as the difference between the fitted values of the full econometric model and the predicted values obtained from a restricted version of the same model where the coefficients of the crime variables have been alternatively set equal to zero. We could thus obtain a list of anomalous municipalities on the basis of the "excess cash inflows", that is the share of cash deposits unexplained by the structural component and correlated to indicators of criminal activity.

The results have not only confirmed patterns already known, but have also provided some new insights. In particular, with regard to cash inflows related to *power crimes*, the most anomalous municipalities have been found to be concentrated in the South, but their presence is not negligible also in the North and Centre. On the other hand, the municipalities with the most significant cash flows related to *enterprise crimes* are located not only in the wealthy Northern districts of the country, but also in several Southern municipalities, most notably around Naples. The anomalies at municipal level have also been aggregated at provincial level, to provide a broad picture of the phenomenon over the national territory.

Additionally, an alternative anomaly-detection methodology has been applied, based on the estimation residuals from a model including only economic fundamentals and other structural, 'physiological' determinants of cash use as regressors, *without* the indicators of criminality. In this way, the hypothesis that the proceeds of criminal activity are laundered via cash locally (i.e., where the crimes are carried out) is released. As a result, with such indicator wealthy Northern regions feature more extensively in the distribution of cash anomalies, compared to maps based on the other approach.

Finally, we analysed the relationship between cash inflows and suspicious transaction reports (STRs). Cash deposits have been shown to be positively correlated with the relevance of local money laundering activity, as proxied by the average riskiness of locally-generated reports. However, such positive relationship wanes for increasing levels of STRs riskiness, implying that cash is a good indicator for potential money laundering-related financial conducts only up to a certain level of riskiness. As also operational experience at UIF suggests, high-profile money laundering cases typically involve more complex financial transactions.

The contribution of this paper to the economic literature is twofold. Firstly and foremostly, it expands previous works on crime-driven cash demand in Italy by providing estimates at municipality level. As a result, the estimation accuracy has significantly improved not only from a statistical viewpoint, but also with regard to the effectiveness in pinpointing the areas where cash-related anomalies are more widespread. Secondly, results suggest that the two classes in which criminal conducts are distinguished (respectively, *power* and *enterprise* crimes) have a positive marginal impact on cash use, which is mostly decreasing for *power* and increasing for *enterprise*. Such evidence seems to match nicely with what one would expect, taking into account the differing characteristics and financial implications of the two types of illegal activity.

More notably, the results of this paper have several operational implications from an anti-money laundering perspective. They allow to build indicators of risk which can be quite useful in steering the intervention of anti-money laundering authorities at several levels. For example, as already emphasized, preliminary results of the research presented in this paper have been used in the recent National Risk Assessment (NRA) for money laundering and terrorism financing, that Italy carried out in 2014 as requested by new international standards (see section 4). More in particular, the identification of anomalous cash payments at a very disaggregated level may represent a potentially powerful tool to use when planning and implementing on-site inspections for checks on intermediaries' anti-money laundering compliance by UIF; it might also contribute to direct on-site and off-site banking supervision on AML matters by the Central bank. To this aim, the model proposed in this study might be usefully developed to be applied to more recent years and at a more disaggregated level. For example, starting from 2012, the SARA data include information also on the intermediary's branch where the individual transactions took place, which implies that anomalies may be detected at a highly refined level of detail. As another example, the evidence on local anomalies and outliers identified with the methodology proposed in this paper might contribute to targeting the activity of law enforcement and judicial authorities.

The line of research presented in this paper could be further extended in several directions. From a methodological point of view, a more comprehensive (and potentially effective) analysis of the relationship between cash use and criminal activity could be achieved by adopting a wider geographical framework. Cash proceeds from illegal activities are not necessarily used in the same place where those activities take place, as our model implicitly assumes. By relying on Local Labour Systems (*LLS*)[27] — which are economically homogenous areas spanning across

[27] "Local labour systems are sub-regional geographical areas where the bulk of the labour force lives and works, and where establishments can find the largest amount of the labour force necessary to occupy the offered jobs. They respond to the need for meaningfully comparable sub-regional labour market areas for the reporting and analysis of statistics" (http://www.istat.it/en/archive/142790). This definition is consistent with the notion of "functional

administrative and geographical boundaries — stronger and statistically significant correlations between criminal conducts and the cash flows they give rise to may be established, thus helping identify each LLS' financial hub at municipal or even branch level.

Finally, as a contribution to the literature on the economics of crime, extending the analysis to more recent years would imply that the effect of the recent Italian economic downturn of 2011-2014 could be accounted for. Recent empirical evidence for Italy shows that the link between downturns and crime is heterogeneous across different areas, but nonetheless weaker in areas with a more marked presence of organised crime (De Blasio and Menon, 2013). By using excessive cash deposits as a proxy for criminal activities, additional insight could be provided on this issue.

region", defined as a territorial unit resulting from the organization of social and economic relations in that its boundaries do not reflect geographical particularities or historical events (OECD, 2002b).

Appendix

Table A1
OLS Estimates

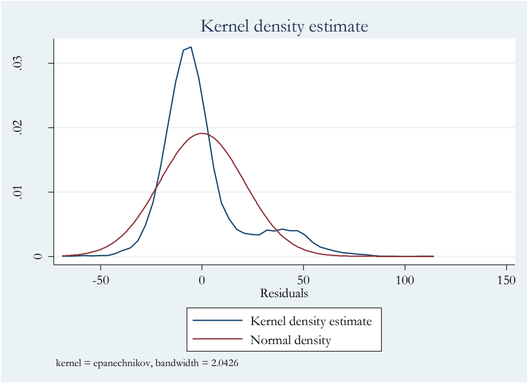
	OLS1		OLS2	
	Coef.	**S.E.**	**Coef.**	**S.E.**
YPC	-0.003***	*0.001*		
ELECT	-0.001***	*0.001*		
BCOUNT	0.384***	*0.027*		
Ln(YPC)			-5.405***	*0.474*
Ln(ELECT)			-10.929***	*0.089*
Ln(BCOUNT)			-9.815***	*0.253*
COAST	1.426**	*0.657*	4.617***	*0.352*
MOUNT	6.465***	*0.546*	1.958***	*0.251*
ENT[a]	0.047**	*0.022*	0.575***	*0.094*
ENT^2			-0.002***	*0.000*
POW [a]	0.281***	*0.065*	3.307***	*0.767*
POW^2			-1.184***	*0.408*
Ln(BUILD)			1.719***	*0.227*
CONS	50.194***	*1.134*	188.620***	*3.891*
R^2	0.299		0.837	
Obs.	6,810		6,576	

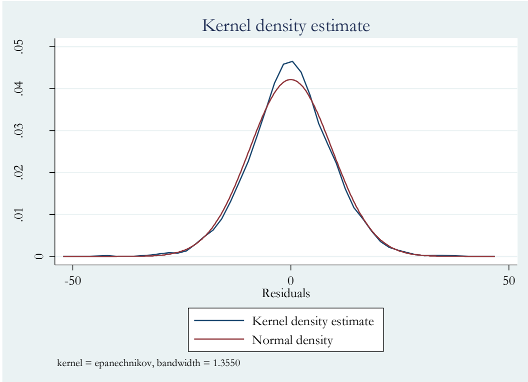
[a] ENT and POW are weighted by an income concentration index in Model OLS1, defined as the ratio of municipal taxable income to is sample mean. The standardization allows for better comparing municipalities with remarkable differences in the level of socio-economic development as well as crime detection and contrasting, thus avoiding automatically assuming higher levels of crime (and money laundering) for municipalities with the number of detected offenses above the sample mean (Ardizzi et al., 2014b).

Figure A1
OLS1 and OLS2 residual analysis

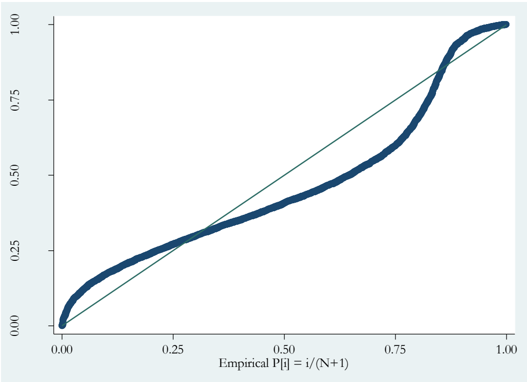
OLS1	OLS2
Shapiro-Wilk test for residual normality*	
Obs: 6,810 W: 0.888 z: 15.853 p-value: 0.000	Obs: 6,576 W: 0.993 z: 8.444 p-value: 0.000

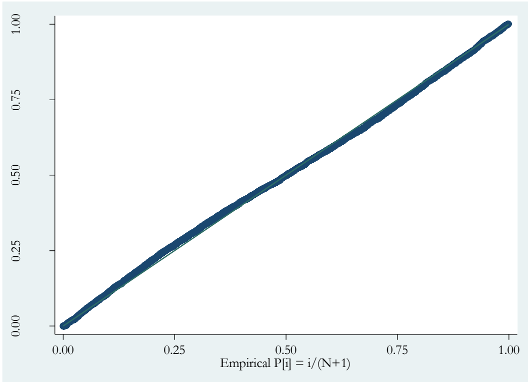
Kernel density estimate



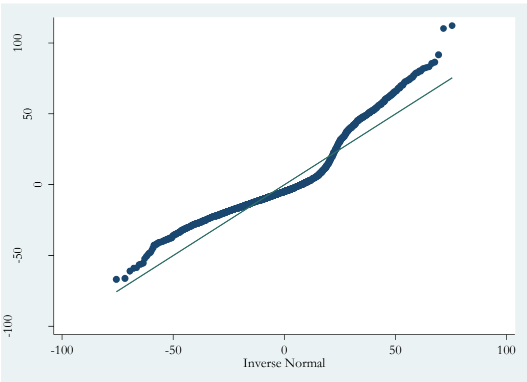


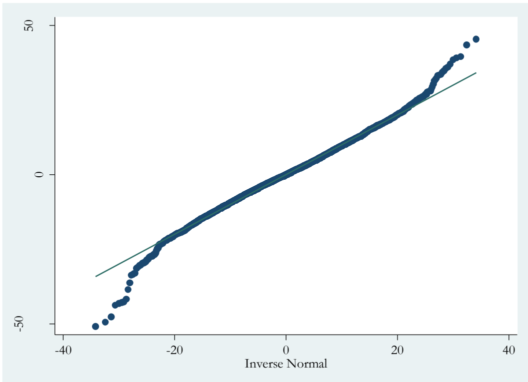
P-P plot





Q-Q plot





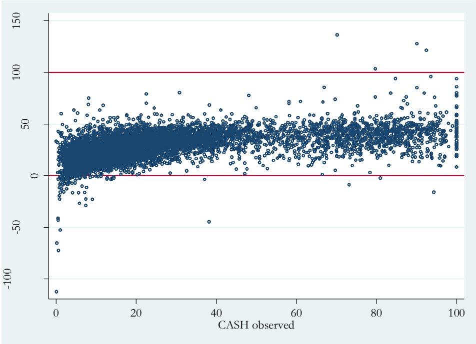
Breusch-Pagan test for heteroscedasticity

OLS1	OLS2
$\chi^2 = 343.3$ Prob > χ^2 = 0.000	$\chi^2 = 164.1$ Prob > χ^2 = 0.000

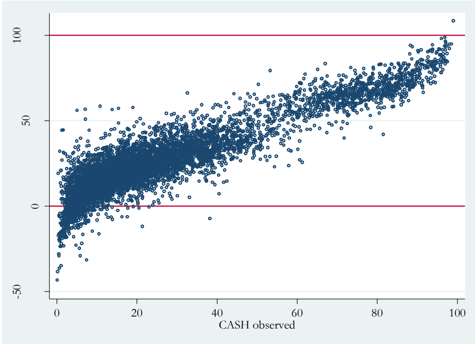
* Since it overestimates non-normality for big sample size (more than 2,000 observations) we also give three graphical evidences.

Figure A2
Estimated and observed values of the dependent variable (*CASH*)*

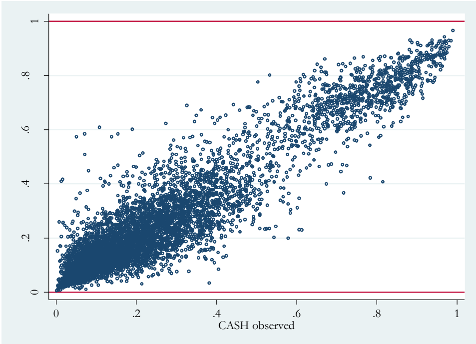
OLS1



OLS2



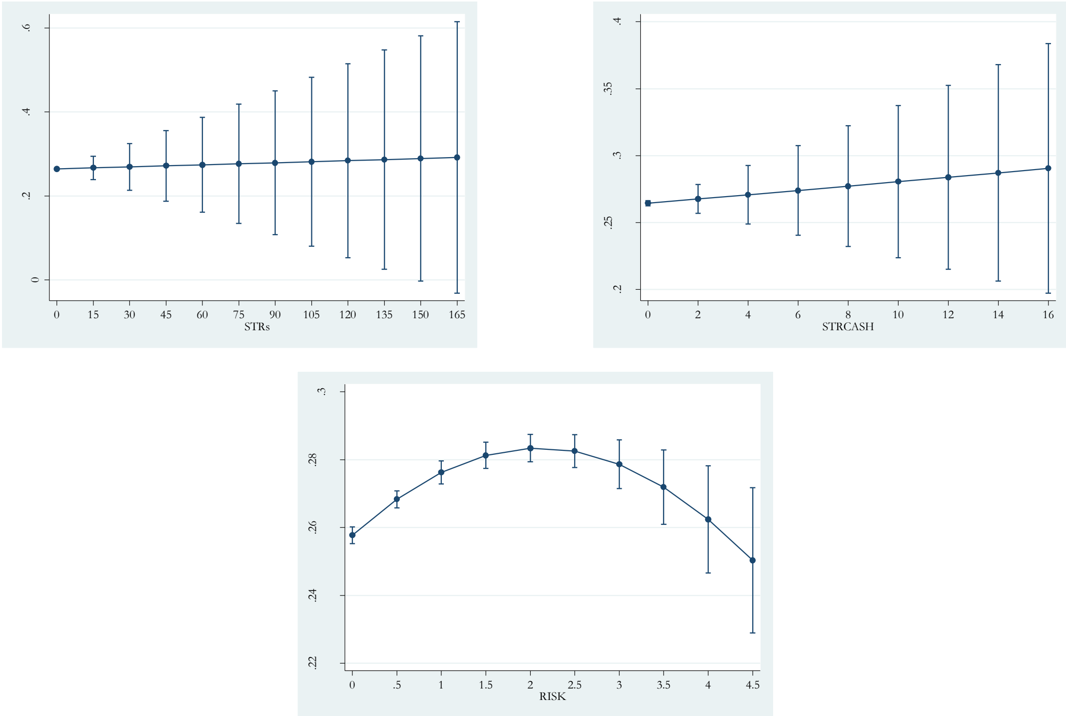
GLM*



* Table 2 estimates.

Figure A3

Cash predicted mean ve*rsus* GLM Predictors*



* Table 4, model (3) estimates; AME conditional marginal effects with 95% CIs.

References

Alvarez F. and Lippi F. (2009), "Financial Innovation and the Transactions Demand for Cash." *Econometrica*, 77(2), pp. 363-402.

Ardizzi G., Petraglia C., Piacenza M. and Turati G. (2014a), "Measuring the Underground Economy with the Currency Demand Approach: A Reinterpretation of the Methodology, with an Application to Italy." *Review of Income and Wealth*, 60(4), pp. 747-772.

Ardizzi G., Petraglia C., Piacenza M., Schneider F., and Turati G. (2014b), "Money Laundering as a Crime in the Financial Sector: A New Approach to Quantitative Assessment, with an Application to Italy." *Journal of Money, Credit and Banking*, 46(8), pp. 1555-1590.

Asmundo A. (2011), "Indicatori e costi di criminalità mafiosa. Analisi ed evidenze empiriche (2004-2007)." In AA. VV., *Alleanze nell'ombra. Mafie ed economie locali in Sicilia e nel Mezzogiorno*, Donzelli.

Block A. (1980), *East Side – West Side. Organizing Crime in New York 1930-1950*. Cardiff: University College Cardiff Press.

Capasso S. and Jappelli T. (2013), "Financial Development and the Underground Economy." *Journal of Development Economics*, 101, pp. 167-178.

Cassetta A., Pauselli C., Rizzica L., Tonello M. (2014), "Financial flows to tax havens: Determinants and anomalies." *UIF, Quaderni dell'antiriciclaggio, Collana Analisi e Studi*, n. 1.

De Blasio G. and Menon C., (2013), "Down and out in Italian towns: Measuring the Impact of Economic Downturns on Crime." *Temi di discussione* (Working papers) no. 925, Bank of Italy.

European Central Bank (2008), *Economic Bulletin*, Special edition, May.

European Central Bank (2011), "The Use of Euro Banknotes − Results of two Surveys among Households and Firms." *Monthly Bulletin*, pp. 79-90, April.

Gambetta D. (1993), *The Sicilian Mafia. The Business of Private Protection*. Cambridge: Harvard University Press.

Humphrey D.B., Pulley L.B. and Vesala J.M. (1996), "Cash, Paper, and Electronic Payments: A Cross-Country Analysis." *Journal of Money, Credit and Banking*, 28(4), pp. 914-939.

Lippi. F. and Secchi A. (2008), "Technological Change and the Demand for Currency: An Analysis with Household Data." *Temi di discussione* (Working papers) no. 697, Bank of Italy.

Masciandaro D., Takáts E. and Unger B. (2007), *Black Finance. The Economics of Money Laundering*. Cheltenham, UK: Edward Elgar.

Mustard D. B. (2010), "How Do Labor Markets Affect Crime? New Evidence on an Old Puzzle." In B.L. Benson and P.R. Zimmerman (eds.), *Handbook on the Economics of Crime*. Elsevier.

OECD (2002a), *Measuring the Non-Observed Economy – A Handbook*. Paris.

OECD (2002b), *Redefining Territories: Functional Regions*. Paris.

Papke L.E. and Wooldridge J.M. (1996), "Econometric Methods for Fractional Response Variables with an Application to 401(k) Plan Participation Rates." *Journal of Applied Econometrics*, 11(6), pp. 619–632.

Schmiedel H., Kostova G. and Ruttenberg W. (2012), "The Social and Private Costs of Retail Payment Instruments. A European Perspective." *ECB Occasional Paper Series*, no. 137.

Schneider F. (2010), "Turnover of Organized Crime and Money Laundering: Some Preliminary Empirical Findings." *Public Choice*, 144(3), pp. 473-486.

Schneider F. and Windischbauer U. (2008), "Money Laundering: Some Facts." *European Journal of Law and Economics*, 26(3), pp. 387-404.

Stix, H. (2004), “How Do Debit Cards Affect Cash Demand? Survey Data Evidence.” *Empirica*, 31(2), pp.93–115.

Tanzi V. (1980), “The Underground Economy in the United States: Estimates and Implications.” *Banca Nazionale del Lavoro Quarterly Review*, 135, pp. 427-453.

Tanzi V. (1997), “Macroeconomic Implications of Money Laundering.” In E.U. Savona (Ed.), *Responding to Money Laundering, International Perspectives*, 91-104. Amsterdam: Harwood Academic Publishers.

Torgler B. and Schneider F. (2009), “The Impact of Tax Morale and Institutional Quality on the Shadow Economy.” *Journal of Economic Psychology*, 30(2), pp. 228-245.

Unger B. (2007), *The Scale and Impact of Money Laundering*. Cheltenham, UK: Edward Elgar.

Walker J. (1999), “How Big is Global Money Laundering?” *Journal of Money Laundering Control*, 3(1), pp. 25-37.

Walker J. and Unger B. (2009), “Measuring Global Money Laundering: ‘The Walker Gravity Model.” *Review of Law and Economics*, 5(2), pp. 821-853.

Zizza R. (2002), “Metodologie di stima dell’economia sommersa: un’applicazione al caso italiano.” *Temi di discussione* (Working papers) no. 463, Bank of Italy.