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EUROSISTEMA

UIF
Unità di Informazione Finanziaria per l'Italia

# Quaderni dell'antiriciclaggio

Analisi e studi

## Cash use and money laundering: An application to Italian data at bank-municipality level

Michele Giammatteo

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# CASH USE AND MONEY LAUNDERING: AN APPLICATION TO ITALIAN DATA AT BANK-MUNICIPALITY LEVEL

by M. Giammatteo*

## Abstract

The payment industry has undergone a radical turnaround as of late, but cash is still considered the king of the means of payment, especially with reference to the underground and illegal economy. This paper aims at (i) measuring the scale of anomalous (and hence potentially associated to unlawful activities) cash usage with reference to Italian banks and municipalities in 2015 and (ii) providing money laundering risk indicators accordingly. By relying on data on cash deposits at single bank branches and developing the methodology introduced in a previous study, we distinguish between legitimate and illegitimate cash flows: the former are those that can be explained on account of local socio-economic fundamentals, the latter are those that the same fundamentals cannot systematically account for. We derive municipal and provincial money laundering risk indicators, whose distribution is found to be consistent with the investigative evidence on Italy's mafia-style criminal organisations and correlated with banks' suspicious transaction reports and some local indicators of crime, which further validate our empirical findings. Indicators have a high potential operational relevance, since they may provide the authorities involved in the anti-money laundering system with an additional tool to carry out their activities on the basis of a robust risk-based approach.

## Sommario

In epoca recente il settore degli strumenti di pagamento è stato interessato da cambiamenti radicali, ma il contante rimane un importante mezzo di regolazione delle transazioni, soprattutto nell'economia illegale. Questo studio ha l'obiettivo di stimare l'utilizzo anomalo di contante (potenzialmente connesso ad attività illecite) e calcolare degli indicatori di rischio di riciclaggio. Utilizzando dati disaggregati sull'operatività bancaria e affinando un modello econometrico introdotto in un precedente studio, i flussi osservati di contante sono confrontati con quelli 'fisiologici' attesi dal modello sulla base dei 'fondamentali' socio-economici e finanziari a livello locale: la discrepanza tra il valore atteso e quello osservato fornisce una misura dei flussi di contante anomali. Sulla base dei risultati vengono elaborati indicatori di esposizione al rischio di riciclaggio a livello di comune e provincia. La distribuzione geografica del rischio risulta coerente con la presenza delle principali organizzazioni mafiose così come emerge dalle evidenze investigative e positivamente correlata sia con misure del riciclaggio (le operazioni sospette segnalate alla UIF) sia con indicatori di attività criminale (le denunce di particolari reati). Gli indicatori possono contribuire a orientare l'azione di contrasto al riciclaggio da parte sia della UIF e delle altre autorità, sia del settore bancario. Il modello è stato stimato sui dati del 2015; sono in corso aggiornamenti su dati più recenti.

**JEL Classification**: E26, E42, G28, K42.
**Keywords**: Money laundering, Crime, Risk-based approach, Cluster random effects.

* UIF (Italian Financial Intelligence Unit), Bank of Italy, Analysis and Institutional Relations Directorate.

## Contents

## 1. Introduction[1]

This study offers a contribution to the economics of money laundering, by applying statistical methods to the objective of identifying illicit funds. In particular, it sets up an econometric model based on data of cash deposits, which are detailed at a level of single bank branch, and goes on to construct risk indicators for banking intermediaries operating in each Italian municipality for the detection of the potential surfacing of underground cash streams.

Innovating from previous works, indicators' reliability and empirical nexus with the phenomenon under investigation (i.e. money laundering) are measured against some proxies of criminal activity and money laundering, also through a multivariate approach; furthermore, they are assessed vis-à-vis the investigative evidence provided by a major Italian law enforcement agency on the diffusion of mafia-style criminal organisations across Italy's various regions.

The econometric analysis implemented aims at suggesting a robust methodology for the identification of possible financial flows somehow related to money laundering. It's worth clarifying that our proposed model is not aimed at detecting single anomalous financial transactions, but rather at identifying where cash streams resulting from illegal activities surface, irrespective of the complexity of the underlying money laundering operation, of the geographical location where the predicate offences are committed or criminals are caught by police.

The ultimate scope of such exercise, from the point of view of the authorities involved in the anti-money-laundering system, is manifold. It can provide a useful tool to carry out the prevention and contrast of money laundering on the basis of a robust risk-based approach. For instance, the indicators could be used by supervisory authorities (in some countries, the Financial Intelligence Unit, or FIU) in planning and implementing on-site inspections for checks on intermediaries' anti-money laundering compliance. Also obligated entities can reap some benefits, since, in accordance with the same risk-based principle, they are required to modulate their controls taking into account the degree of money laundering risk characterising the territories where they actually operate. To this scope, the identification of anomalous cash inflows at a very disaggregated level, and the resulting definition of local risk indicators, may represent a potentially powerful tool.

The rest of the work is structured as follows: Section 2 presents the research question, illustrating the relationship between cash use and money laundering; Section 3 describes the conceptual framework and the data used in the analysis; Section 4 introduces the econometric model and shows the empirical findings; Section 5 presents the methodology used for the computation of our risk indicators for municipalities and provinces; in addition, indicators' reliability is assessed against investigative evidence and some measures of 'illegal conducts' at local level; Section 6 contains some brief concluding remarks.

## 2. Is cash still king?

The aim of this paper is that of trying to identify anomalous use of cash potentially connected to illicit activities, at a high level of detail. Before illustrating how we embark in this pursuit and the results we obtain, we need to answer two key questions: why is it relevant to do it? What is the underlying rationale for this exercise?

For years on end cash has been traditionally considered predominant among the means of payment, mainly due to its ability to ease both legal and illegal transactions. However, during the last

[1] The views and the opinions expressed in this paper are those of the author and do not necessarily represent those of the institution he is affiliated with. I wish to thank for their useful comments Domenico J. Marchetti, Mario Gara, a referee, the seminar participants at UIF, the IV Workshop UIF-Bocconi "Quantitative methods and the fight against economic crime", the IRCrES-CNR International Workshop on Computational Economics and Econometrics (IWcee18) and the 35th EALE Annual Conference (2018). My thanks to Major Gaetano Licari (Department Analysis, *ROS – Carabinieri*), who provided a crucial contribution to Section 5.2.

decade radical changes in the provision of financial services and the population's purchasing habits have undermined its leading role, so much so that several experts in the field have announced its progressive decline.[2]

Data and experience, though, seem to provide some crucial qualifications to this picture. For instance, in the 15 years since the introduction of the euro in January 2002 the number of banknotes in circulation rose fourfold[3] and their value as a percentage of euro-area's GDP more than doubled, whilst in the US rose by over 20%.[4] Cash has also enjoyed a sudden additional bout of success during the financial crisis, as a result of the associated uncertainty and the expansionary stance of monetary policy.

Cash grip on power seems to be able to rely on some particularly resilient strongholds even among developed economies, which can be also revealing of the potential dark side of cash force. Italy is a case in point. It features an extremely high percentage use of cash: in 2016, the number of cash operations accounted for 86% of all transactions, corresponding to 68% of the whole value, against a euro-area average of 79% and 54% respectively (Esselink and Hernández, 2017). One of the reasons of this enduring success is typically identified also in the pervasiveness of the country's ill-famed criminal organisations. Traditionally cash is considered to be criminals' favourite means of payment and criminals' earnings mainly take the form of cash; as a result, the more widespread and profitable illegal activities the more cash they generate (FATF, 2015). With reference to Italy, the contribution illegal activities can provide to cash use is approximately measured by their estimated size, which, according to the 2014 periodical National Risk Assessment of money-laundering and terrorist financing risks, range between 2 and 12% of GDP (with most of the available estimates pointing to the upper end of the range), which is equivalent to between 27 and 194 billion euro.

One specific illicit conduct in which cash is particularly key for criminals is money laundering. This is true not only in connection with illicit business readily generating cash proceeds (such as drugs trafficking and extortion) but, as international evidence shows, it applies to almost all types of predicate crime (Europol, 2015).[5] As a result, the illegal demand for cash is further enlarged: although it is hard to "claim that all money laundering involves cash, [...] cash does play an important role in many [money laundering] operations" (Rogoff, 2016).

As a consequence of the very nature of cash, however, its relevance for money laundering may be underplayed if gauged on the basis of the actual cases uncovered involving banknotes, because the direct linkage between suspicious funds and the corresponding predicate offences is often difficult to prove: although umpteen suspicious transaction reports (STRs) on cash transactions crowd the desk of FIUs financial analyst the world over, rarely significant files are extracted from them, unless there is the direct involvement of criminals, which unsurprisingly is rarely the case.

Innovative payment instruments, such as crypto-assets, are enjoying a moderate success also among criminals, and therefore it is argued that cash seems to be inexorably sliding toward irrelevance, for legal and illicit purposes alike. However, not rarely, new technologies and traditional methods are used hand in hand, as they mutually reinforce their specific respective features.[6] *Even the most up-to-date money laundering techniques often require at some stage that financial resources be cashed so as to break any traceable link between the underlying crime and its monetary revenue.*[7] In this view, rather than substitutability, a

[2] See, among other, The Economist, 15 February 2007.

[3] See https://www.ecb.europa.eu/stats/policy_and_exchange_rates/banknotes+coins/circulation/html/index.en.html.

[4] BIS, various issues.

[5] This evidence is also stressed by the last Eurostat Handbook on illegal economic activities in National Accounts and Balance of Payment (2018): "Almost all crime types make use of cash to facilitate money laundering, even if not all are readily cash-producing criminal businesses."

[6] The joint use of pre-paid cards and cash is a typical example of different tools used sequentially in order to conceal origin of illicit funds. As shown in the Europol 2015 report, this can be the case also for trade-based money laundering, investment in real estate, and the use of virtual currency.

[7] This is even true for cybercrimes (phishing or hacking): they do not generate directly cash proceeds, but cash is somewhere necessary to disguise the criminal source by allowing the erasing of the digital footprint. See also "Crypto money-laundering", The Economist (April 27, 2018).

complementarity relationship would emerge between cash and alternative payment instruments.

On account of all the above, we can easily answer the first question we asked at the beginning of the paragraph: in spite of all the most recent developments in the payment sphere, cash does certainly play an important role as far illegal transactions are concerned. Hence, trying to quantify to what extent that is the case is certainly a relevant goal to pursue, at least from the perspective of the authorities and all other operators and institutions involved in fighting money laundering and financial crime.

But what has been said so far could also provide useful clues as for the answer to the second issue we raised, i.e. the search for a rationale for our exercise. In order to provide the measure of illegal proceeds taking the form of cash at a local level, rather than seeking a direct connection between cash and the criminal activities it is related to, it may be more appropriate to establish an indirect link, under the assumption that illegal cash gains will be somehow expended for the purchase of goods and services and are very likely to be eventually deposited at a bank. Once the overall cash usage in a certain area, as measured by observed cash deposits at local credit institutions, is discounted for the share which appears consistent with the economic and social landscape of that area (including its grey economy), all that remains unaccounted for may be considered to be potentially connected to illegal activities, which may take place in the same area or elsewhere, in the absence of barriers to the free movement of funds within a country. [Likewise, once the flow rate of a river is traced back to all known tributaries, all what remains unaccounted for need necessarily be provided by some previously ignored underground streams, which can thus be sought for so as to eventually identify its origin.]

Most of the times the actual application of an approach of this kind is severely crippled by the widespread lack of detailed information about cash and its local use. Existing empirical evidence is usually confined to general statistics provided at national or supranational aggregate level, sometimes disaggregated with respect to banknote denomination, economy sector, final users' characteristics or consumer habits. Thanks to the availability of rich information on payment instruments usage at local level in Italy, the econometric analysis proposed in this work allows us to discriminate between legitimate and illegitimate cash flows, making it possible to isolate the size of cash transactions of possible illegal origin.

## 3. Conceptual framework and data

In what follows we develop a framework aimed at analysing the relationship between the use of cash – as measured against the use of other means of payment – and a set of local economic and financial features. Our approach originates from the revised *currency demand* approach proposed by Ardizzi et al. (2014) and further develops the methodology proposed in a previous study of ours (Ardizzi et al., 2018), by fitting more granular data and thus focusing on more disaggregate risk indicators.

As the main difference with those approaches, in the set of explanatory variables the econometric model shown below includes only proxies of the 'legal or quasi-legal' components of cash use, thus excluding any reference to the 'illegal' component. As stated below in Section 5, the immediate consequence of such approach is that of deriving money laundering risk indicators which are *independent* of any geographical distribution of crimes, namely defined on the basis of a 'residual' component netted of the erratic component of the regression model.

### *3.1 The dependent and explanatory variables*

Our variable of interest is the ratio between cash inflows and non-cash (hereafter electronic) inflows observed at each bank branch, that is

$$cash\ ratio = cash\ inflows/electronic\ inflows \qquad [1]$$

which, by construction, assumes non negative values.

Unlike Ardizzi et al. (2014 and 2018, Section 2) where the regressors used in the econometric specification aim at capturing both the legal and illegal motivations underlying the use of cash, in the following model we consider only the variables that in the existing literature are considered proxies of the legal component. This is because, as already mentioned, instead of looking for a direct connection between cash and criminal activities at local level we develop a statistical methodology for 'daylighting' underground cash streams irrespective of (free from) the distribution of crimes at local level.

To this end, the set of our covariates includes (see Ardizzi et al., 2018): i) the per capita personal taxable income (*income per capita*), which can be considered a proxy of local socio-economic development; ii) the value of non-cash bank transactions (*electronic payments*) — which is alternatively divided by the number of total transactions observed for each bank branch or by the number of all bank branches in a province — measuring the attitude of bank customers toward the use of payment instruments different from cash; iii) the per capita number of bank branches (*branches per capita*) observed in each municipality and iv) the total number of transactions observed in each bank branch (*transactions*), which proxy the level of financial inclusion and deepening at municipality and branch level respectively. In line with the literature, the expected relationship of all these variables with the response variable is negative; they are highly correlated with, respectively, economic development, general education and financial literacy, leading in general to a lower use of cash and greater confidence in alternative payment instruments (Humphrey et al., 1996; Stix, 2004; Ardizzi et al., 2018).

In addition, two dummy variables are introduced in order to account for geographical-specific factors related to coastal (*coast*) and mountain (*mountain*) municipalities. *Ceteris paribus,* coastal municipalities are thought to be characterized by non-residents' cash-intensive demand for goods and services due to touristic activities, whereas in mountain municipalities a more difficult access to banking services might require that greater cash stocks are held.

An additional control variable captures the role played locally by the shadow economy. Our intention is that of singling out cash proceeds coming from the underground economy (a 'quasi-legal' factor) so as to concentrate the analysis exclusively on those originating from strictly defined criminal activities. To this end, we use the share of firms operating in building, trade and restaurants in each municipality (*shadow economy*). These are traditionally the sectors in which the number of irregular workers is wider and their cumulative size can be fruitfully deployed as a good proxy for evasion of taxes and social contributions.

Finally, a set of dummy variables are introduced to control for specific financial features related to different bank types (*bank type*) according to a classification of Italian banks developed for specific money laundering oversight purposes by the UIF, that combines their size, type of activity and geographical location.[8] The underlying rationale is that all these factors can influence the propensity to use cash by the banks' customers.

### *3.2 Data*

The main source of data used in our analysis is the Aggregate Anti–Money Laundering Reports (SARA in the Italian acronym) database. Under the Italian anti-money laundering law (Legislative Decree no. 231/2007), banks and other financial intermediaries have to report monthly to Italy's Financial Intelligence Unit (UIF) all transactions amounting to over 15,000 euros, after aggregating them by branch, customer sector and type of transaction.[9]

The data for all variables defined at bank branch level were collected from the SARA database (see Table 1 for details). As for other variables, data on local personal taxable income were acquired from the Italian Internal Revenue Agency ("*Agenzia delle Entrate*") website. Municipalities' resident population (which is used for normalizing most of the variables), the two dummies identifying coastal and mountain

[8] The classification distinguishes several categories of banks, which include major nation-wide banks, special purpose banks and branches of foreign banks; all remaining (local) banks are divided into 5 macro-regions, according to where most of the respective activity takes place. In turn, each of all categories (with the only exception of major nation-wide banks) is divided in two sub-groups (*big* and *small*) based on bank's size; overall, therefore, the classification has 15 bank groups.

[9] In 2015, the year of analysis, UIF received 101 million aggregate records, corresponding to 329 million individual transactions worth 21 trillion euro.

municipalities and the number of firms operating in building, trade and restaurants were obtained from the website of the Italian National Institute of Statistics (ISTAT).[10]

All data used in the empirical analysis refer to 2015 (the only exception being the proxy of shadow economy, for which, at the time of the analysis, the most recent data available were those of 2014).[11]

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

**Table 1**
**List of variables and summary statistics**
(2015)

| Variable | Note | Source | Mean | Median | Sd |
|---|---|---|---|---|---|
| ***Bank branch level*** | | | | | |
| *cash inflows* | *€ millions* | UIF | 4.03 | 0.96 | 27.45 |
| *electronic inflows* | *€ millions* | UIF | 121.90 | 12.31 | 2,657.00 |
| *cash ratio* | *Cash inflows / electronic inflows* | UIF | 4.67 | 0.11 | 318.22 |
| *transactions* | *Number of total transactions* | UIF | 5,807 | 1,865 | 38,335 |
| *electronic payments* | *Value of electronic inflows over the number of branch transactions (€)* | UIF | 9,083 | 6,800 | 39,483 |
| *bank type* | *Categorical: type of bank* | UIF | - | - | - |
| ***Municipality level*** | | | | | |
| *income per capita* | *Per capita personal taxable income (€)* | Revenue Agency | 13,569 | 13,783 | 3,451 |
| *branches per capita* | *Per capita number of bank branches x 10,000 inhabitants* | ISTAT | 11.70 | 10.44 | 7.07 |
| *coast* | *Dummy: coastal municipality* | ISTAT | 0.24 | 0.00 | 0.43 |
| *mountain* | *Dummy: mountain municipality* | ISTAT | 0.19 | 0.00 | 0.39 |
| *shadow economy* | *Share of building, trade and restaurant firms on total municipality firms* | ISTAT | 0.47 | 0.45 | 0.09 |
| ***Provincial level*** | | | | | |
| *electronic payments* | *Value of electronic inflows over the number of branches in a province (€ millions)* | UIF | 102.50 | 44.42 | 149.90 |

Source: authors' own calculations on UIF, ISTAT and Internal Revenue Agency data.

The final sample considered for the econometric analysis – net of municipalities and banks for which data on at least one variable were not available – contains 45,485 observations at branch level, which span over 7,440 municipalities (92% of all municipalities in Italy in the year of analysis) and 562 banks (85% of all banks[12]). Since there are many cases of banks with multiple branches within a given municipality, the total number of bank-municipality pairs amounts to 29,226.

[10] Observe that the impact on value added of the Italian shadow economy is particularly high in these sectors. Agriculture is a sector surely featuring a high share of informal employment. However, ISTAT does not provide data at municipality level and official statistics point out the modest agriculture contribution to the size of national value added (see ISTAT, 2017).

[11] The municipal distribution of firms operating in building, trade and restaurants is highly stable across years, so as to attenuate significantly the problem of using 1 year-lagged data.

[12] [The 15% of banks left out of the sample refers to banks which operate only within municipalities for which data are not available, plus few banks which do not operate in cash.]

## 4. The econometric model

### *4.1. Empirical strategy*

The econometric analysis is carried out by estimating the simplest version of a *mixed model*, namely a *linear random effect* model. The model accounts for two different effects, fixed and random: the former provides the estimates of intercept and slopes of the population as a whole (as in ordinary regressions), while the random coefficients are allowed to vary across *clusters* of elementary branch-level units so as to capture unobserved heterogeneity at an aggregate level. This estimation method is thus crucially different from those of Ardizzi et al. (2014 and 2018), where the analysis was performed on data at the level of, respectively, provinces and municipalities; the use of branch-level data in our study also allows for computing more accurate indicators of money laundering risk, as it will be seen below in Section 5.

Mixed models can be thought of as a *latent variable models* where a generic response variable is regressed on observed covariates, whilst some other relevant unobserved covariates are excluded, thus leading to unobserved heterogeneity. When the heterogeneity refers to groups of elementary units, intra-cluster dependence among the responses can typically arise.[13] In presence of a hierarchical structure of the data it is possible to introduce *cluster*-specific *effects* in order to account for constant unobserved determinants and – if relevant for the research scope – to estimate the corresponding *random effects* in addition to the population-averaged fixed effects.

Consider the theoretical framework described above and the following hierarchical structure of the data. Elementary units ($i = 1, \dots, n_j$) defined at bank branch level are nested in the groups ($j = 1, \dots, J_m$) defined by pairs of banks and municipalities. The outcome variable of the model (*cash ratio*) is defined as the natural logarithm of [1], that is the ratio between cash and electronic inflows at bank branch level. Let the subscript *m* denote the municipality level. Then, we propose the following basic specification of a *two-level random intercept model*:

$$
\begin{aligned}
cash\,ratio_i = \beta_0 &+ \beta_1 income\ per\ capita_m + \beta_2 branches\ per\ capita_m + \beta_3 electronic\ payments_i \\
&+ \beta_4 transactions_i + \beta_5 COAST_m + \beta_6 MOUNTAIN_m \\
&+ \beta_7 shadow\ economy_m + BANK\ TYPE\ dummies_i \\
&+ u_j + \varepsilon_i \qquad [2]
\end{aligned}
$$

where all the continuous covariates (indicated in lowercase letters) have been transformed in their natural logarithms[14]. The geographical dummy variables *COAST* and *MOUNTAIN* assume the value of 1 when the municipality is, respectively, on the coast or in the mountains and 0 otherwise,[15] while the *BANK TYPE* dummies correspond to the categories of the bank classification being used. The regression coefficients $\beta$'s represent the conditional (fixed) effects of the independent variables given the values of the random effects $u_j$, which in turn can be interpreted as measuring bank-municipality constant (unobserved) effects.[16]

Random intercept models rely on the fundamental hypothesis of independence between covariates and cluster residuals ($E[u_j|x] = 0$). The violation of this assumption – that is, the presence of any correlation between cluster residuals and covariates – usually leads to the adoption of fixed-effects estimation strategy, ensuring that unbiased estimates of the regression coefficients are obtained by

[13] This typically leads to dependence between responses for units grouped in the same cluster, standard error underestimation of regression coefficients and, as a consequence, overstatement of statistical significance.

[14] In this benchmark specification electronic payments are defined at the branch-level; as already mentioned, we also run regressions with electronic payments at the province-level.

[15] A municipality is classified as 'mountain' when it reaches an altitude of at least 600 metres in the North and 700 in the Central and Southern regions. Note that a municipality can be simultaneously coastal and mountain, or neither of them.

[16] As usual for random effects models, it is assumed that the clusters *j* are independent and that the total and group residuals are distributed as $\varepsilon_i|x \sim N(0, \sigma_\varepsilon^2)$, $u_j|x \sim N(0, \sigma_u^2)$.

eliminating the heterogeneity bias altogether.[17] According to the relevant literature (Mundlak, 1978; Skrondal and Rabe-Hesketh, 2004; Bell and Jones, 2015), estimating a fixed-effect model is neither the only option available nor the most effective. Indeed, a random effects approach – generally providing consistent and efficient estimates – has to be preferred under specific conditions (the dataset is unbalanced; group-invariant characteristics which cannot be explored through a fixed effect approach are used as regressors; the research focusses on cluster specific effects), which are all fully met in our case, definitely supporting the choice of a random effects estimation[18].

### *4.2 Estimation results*

Two alternative specifications of the random effects model [2] were estimated, each including a different definition of the variable *electronic payments*: in the first model we consider the value of electronic inflows over the number of total transactions observed at bank branch level (*electronic payments at branch level*); in the second model we use the total value of electronic inflows over the number of bank branches observed in each province (*electronic payments at province level*). While in the latter case a provincial average attitude to the use of non-cash means of payments is accounted for, the former approach aims at controlling for average customers' financial behaviour at branch level.

Estimates remain consistent irrespective of the specification (see Table 2). More specifically, we get negative and significant relationships between the dependent and the structural variables: higher values of per capita income, per capita number of bank branches, normalized electronic payments and total branch transactions are negatively correlated with the observed relative cash inflows. This result is in line with the expectations and with the existing literature, for which the use of cash is usually negatively correlated with individual income, financial literacy, confidence in alternative payment instruments and financial deepening (Humphrey et al., 1996; Stix, 2004).

The sign of the coefficients for territorial *dummies* and for the proxy of the shadow economy confirms a more intense use of cash, other things being equal, in, respectively, municipalities located in coastal or mountainous areas and in those more exposed to irregular economic activities (Ardizzi et al., 2018).

Obtaining coefficients estimate that match the theoretical hypothesis is obviously important to our end. At the same time, it represents only a minimum requirement that our model should satisfy, since our objective is primarily that of obtaining local indicators of cash-related money laundering risk. In particular, with regard to the (ex-post) random effects estimate, the *Rho* coefficient in Table 2 indicates that between the 12% and 17% of the total model variability can be attached to the specific bank-municipality intercepts.[19] This signals that they have empirical relevance and can be relied upon for defining the anomaly indicators, which will be presented in the next section.

[17] In more general terms, fixed effect estimations provide only within-cluster effects simply removing all cluster variation.
[18] In particular, a) our database features bank-municipality clusters including an extremely varying number of elementary units - in some cases 'singleton clusters' made of just one observation – that, unlike the case of fixed effect specification, can be correctly estimated by random effects procedure, only requiring "*the existence of a good number of clusters of size 2 or more*" (Rabe-Hesketh and Skrondal, 2012); b) many of the model covariates are defined at municipality level; c) our final objective is that of defining bank-municipality risk indicators as resulting from the model's random effects (or rather the empirical Bayes estimates thereof).
[19] Likelihood-ratio tests, comparing the random effects model with ordinary regression, significantly reject the null hypothesis of random effects irrelevance.

**Table 2**
**Model estimates**
(2015)

| | **Model 1** | **Model 2** |
|---|---|---|
| *income per capita* | -0.469*** *(0.040)* | -0.526*** *(0.056)* |
| *branches per capita* | -0.264*** *(0.017)* | -0.407*** *(0.023)* |
| *electronic payments at branch level* | -1.328*** *(0.017)* | |
| *electronic payments at province level* | | -0.061*** *(0.014)* |
| *transactions* | -0.099*** *(0.006)* | *-0.288**** *(0.008)* |
| *COAST* | 0.309*** *(0.022)* | 0.361*** *(0.030)* |
| *MOUNTAIN* | 0.095*** *(0.020)* | 0.048* *(0.026)* |
| *shadow economy* | 0.631*** *(0.063)* | 0.635*** *(0.083)* |
| *BANK TYPE dummies* | Yes | Yes |
| *constant* | 12.923*** *(0.433)* | 3.249*** *(0.512)* |
| *N observations* | 45,485 | 45,485 |
| *N groups* | 29,226 | 29,226 |
| $R^2$ (overall) | 51.7% | 23.9% |
| *Rho* | 16.6% | 11.6% |

Dependent variable: $cash\ ratio = ln(cash\ inflows/electronic\ inflows)$.
Clustered (municipality) standard errors in parentheses.
*Rho:* percentage of total variance of the model due to the random effects.
p-value: *** <0.01, ** <0.05, * <0.1.
Source: authors' own calculations.

# 5. Indicators of anomaly

### *5.1 Computation of risk indicators*

In this section we compute a set of model-based risk indicators for anomalous cash inflows. Starting from the basic indicators of anomaly to be defined at the bank-municipality level, we derive measures of anomalous cash use at municipal and provincial level.

The operational implications of such indicators are manifold. In keeping with international anti-money-laundering standards[20], they might provide the authorities involved in the anti-money-laundering system with an additional tool to plan their activities on the basis of a more effective *risk-based* approach. Likewise, financial intermediaries could benefit from the results of this analysis by raising their awareness at local level on the basis of a geographical distribution of potential money laundering signals.

In previous works (see Ardizzi et al., 2018) the risk indicators are defined by following two alternative methods. In the first approach a model of cash demand is estimated which includes indicators of local criminal activity, in addition to economic and financial variables. The proportion of cash inflows

[20] FATF's Recommendation no. 1 requires that "countries perform a national assessment (NRA) of the risk of money laundering (and terrorism financing) so as to design proportional anti-money-laundering measures and re-allocate resources in the most effective way".

which is 'explained' by the illegal component (*excess cash inflows*) is computed as the difference between the fitted values of the full model (i.e., which includes the crime indicators) and the predicted values obtained from a restricted version of the same equation where the crime variables are set equal to zero. 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 related to some criminal activity. However, by including the number of crimes reported locally among the independent variables one implicitly assume that criminal proceeds are laundered in the same municipality where they are generated and, above all, that criminal proceeds in cash *are strictly proportional to the crimes reported*: as such, the risk indicators provided by such approach have little valued added with respect to the simple raking of municipalities based on crime statistics. In order to overcome these shortcomings, in the second approach the risk indicators are defined on the basis of the estimation residuals of the model excluding the indicators of criminality from the covariates: in this respect they simply represent the share of the response variable which remains *unexplained by economic fundamentals* and other structural factors[21]. However, such 'residual' approach suffers from the possible inclusion of an erratic component in the definition of the risk indicator.

The methodology proposed in this study addresses the deficiencies of both these methods in two ways. Firstly, the estimated equation includes only explanatory variables referring to the structural determinants of cash use (the 'legal or quasi-legal' components), with no indicators of criminal activity: therefore, the resulting risk indicators are not 'constrained' by the territorial pattern of crime data. Secondly, the model-based risk indicators are identified in the *random effects* of the estimated model ($\hat{\boldsymbol{u}}_j$ in the equation [2]). Such *random effects* can be interpreted as cluster-level residual factors of the estimated dependent variable due to *bank-municipality* specific characteristics; they identify a 'systematic residual' component that is left unexplained once the main economic and financial fundamentals are controlled for. Hence, *random effects* are both (i) independent from the geographical distribution of criminal activities (i.e. the 'illegal component') and (ii) net of the erratic component of the regression model by construction.

Clearly, choosing the benchmark specification appropriately is crucial for the definition of our model-based risk indicator. In line with standard practices, whereby the model showing the best fit on the observed data should be chosen, our benchmark specification is Model 1 of Table 2, since it shows a higher value of the fitting measure (*R-squared*) and, at the same time, a greater percentage of total variance of the model due to the random effects (*Rho*).[22]

In our approach, we hold as anomalous the bank-municipality pairs belonging to the 2.5% right-hand tail of the overall random effects distribution (the total number of bank-municipality pairs is 29,226, which corresponds to the number of random effects estimated by the models of Table 2). By way of example the top 20 anomalous positions are listed in Table 3. Obviously, more than one anomaly can be observed in each municipality and, correspondingly, a bank can emerge as anomalous in different municipalities.

In order to provide the indicative magnitude of the anomalous cash flows measured by our indicators, it is possible to compute the corresponding estimated monetary value. This is obtained by inverting[23] and decomposing the dependent variable of equation [2] (the log of cash ratio) as follows:

$$\widehat{cash\ inflows_i} = \{exp(\widehat{\boldsymbol{\beta}}\boldsymbol{X}) + exp(\widehat{\boldsymbol{\beta}}\boldsymbol{X})[exp(\hat{u}_j) - 1]\} \cdot electronic\ inflows_i \qquad [3]$$

[21] This type of approach was first proposed by Cassetta et al. (2014) in their search for anomalies in Italy's foreign wire transfers.

[22] It needs be reminded that the two specifications differ in that bank clients' propensity to use non-cash means of payments is measured at different levels (bank branch in Model 1 vs province in Model 2). Should criminals feature a preference for specific bank branches (for example because branches are located in areas with high crime rates or because the staff is colluded with or intimidated by them), the regressor in Model 1 would capture also anomalies of interest for the analyst. Hence Model 1's better fit could come at the cost of lessening the effectiveness of our risk indicators; however, the higher share of variance explained by random effects in Model 1 than in Model 2 shows that that is not the case. Moreover, investigative evidence (see Section 5) strongly support Model 1's results.

[23] The negative ratios obtained by this step were set equal to a value just above zero (1E-04) in order to avoid meaningless negative cash inflows.

where $\boldsymbol{X}$ is the vector of model covariates, $exp(\widehat{\boldsymbol{\beta}}\boldsymbol{X}) \cdot electronic\ inflows_i$ is the evaluated fixed component of the model, while $exp(\widehat{\boldsymbol{\beta}}\boldsymbol{X})[exp(\hat{u}_j) - 1] \cdot electronic\ inflows_i$ represents the evaluated random component, which is indicated in the last column of Table 3 (summed up at the bank-municipality level).

**Table 3**
**List of top 20 anomalous bank-municipality pairs**
(2015)

| Ranking | Municipality - Region | Bank - Type | Estimated anomalous cash inflows (mls €) |
|---|---|---|---|
| 1 | Municipality 1 - Trentino-South Tyrol | Bank 1 - Special Purpose (*large*) | 0.05 |
| 2 | Municipality 2 - Tuscany | Bank 2 - Special Purpose (*large*) | 13.10 |
| 3 | Municipality 3 - Emilia-Romagna | Bank 3 - North-West (*large*) | 4.76 |
| 4 | Municipality 4 - Emilia-Romagna | Bank 4 - Special Purpose (*large*) | 5.31 |
| 5 | Municipality 5 - Lombardy | Bank 3 - North-West (*large*) | 133.00 |
| 6 | Municipality 6 - Apulia | Bank 5 - Special Purpose (*large*) | 61.00 |
| 7 | Municipality 5 - Lombardy | Bank 6 - National | 81.80 |
| 8 | Municipality 7 - Lazio | Bank 7 - Centre (*large*) | 83.40 |
| 9 | Municipality 2 - Tuscany | Bank 6 - National | 34.70 |
| 10 | Municipality 5 - Lombardy | Bank 8 - National | 1.61 |
| 11 | Municipality 8 - Veneto | Bank 9 - National | 0.79 |
| 12 | Municipality 3 - Emilia-Romagna | Bank 6 - National | 28.90 |
| 13 | Municipality 3 - Emilia-Romagna | Bank 10 - Special Purpose (*large*) | 7.56 |
| 14 | Municipality 5 - Lombardy | Bank 11 - National | 12.30 |
| 15 | Municipality 5 - Lombardy | Bank 12 - National | 156.00 |
| 16 | Municipality 9 - Veneto | Bank 9 - National | 6.87 |
| 17 | Municipality 7 - Lazio | Bank 13 - Centre (*large*) | 504.00 |
| 18 | Municipality 10 - Friuli-Venezia Giulia | Bank 9 - National | 282.00 |
| 19 | Municipality 1 - Trentino-South Tyrol | Bank 6 - National | 8.80 |
| 20 | Municipality 10 - Friuli-Venezia Giulia | Bank 6 - National | 7.15 |

Note: The total number of *random effects* coincides with the number of bank-municipality pairs (29,226).
Source: authors' own calculations.

From the indicators at bank-municipality level illustrated above it is possible to derive *municipal* and *provincial* measures of (cash-related) money laundering risk. As to the latter measure, we compute the share of bank-municipalities identified as anomalous (top 2.5%) over the total number of bank-municipality pairs observed for each province: this seems indeed the most natural measure of risk at provincial level in our context, given the level (bank-municipality) at which we define the concept of anomaly in this paper. For single municipalities, however, this criterion would not be suitable, since a large share of them (67%) has only three banks or less operating in their territory. We therefore chose to consider as 'risky' the municipalities showing at least one bank-municipality anomaly. The rational is that the presence of few anomalies (even a single one) seems enough to qualify a municipality as 'risky', even more so since most of them are small or very small in size.

Figure 1 shows the municipal and provincial distribution of cash-related money laundering risk for Italy in 2015. Since both maps are based on the estimated random effects of an econometric model where the dependent variable is the relative incidence of cash inflows, they provide a measure of the anomalous component of such incidence. In other words, the risk indicators provide a measure of the extent to which any cash deposited in a given municipality or province may be associated to the proceed of some crime.

As an alternative approach, if one is interested in the *size* of anomalous cash flows, rather than their incidence, it is possible to compute risk indicators based on the estimated values of anomalous cash inflows at bank-municipality level described above, i.e. such as those reported in the last column of Table

3. In detail, we aggregate, respectively by municipality and province, the estimated value of the top 2.5% bank-municipality anomalies. The resulting ranking and maps are illustrated in Figure 2.[24]

**Figure 1**
**Risk of money laundering – Bank-municipality anomalies**
(2015)

| Municipalities with bank-municipality anomalies | Share of top 2.5% bank-municipality anomalies over total bank-municipality pairs by provincies |
|---|---|

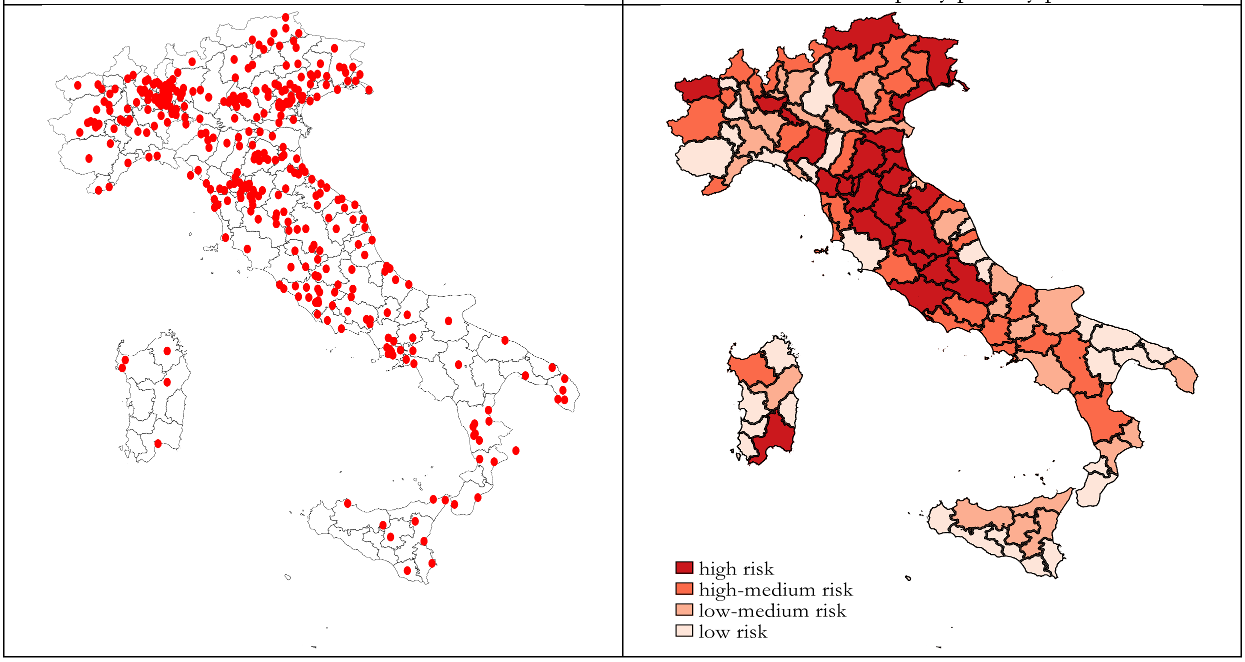
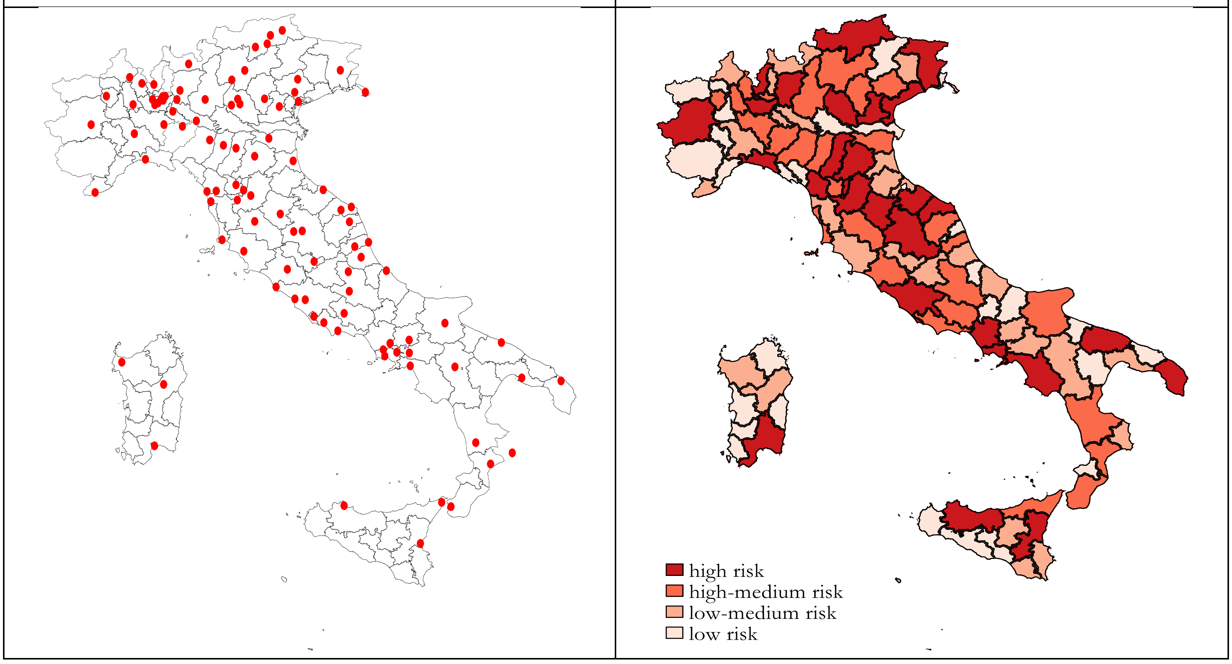



**Figure 2**
**Risk of money laundering – Estimated anomalous cash flows**
(2015)

| Top 100 municipalities | Provincial amounts |
|---|---|




[24] In the left-hand side panel we report the 100 municipalities showing the highest estimated anomalous cash flows; notice that considering all risky municipalities would have simply reproduced the corresponding map of Figure 1.

Both indicators are appropriate for identifying the risk of money laundering, but the choice of using one rather than the other depends on the type of activity they are deployed for. For instance, the first indicator, which measures the incidence of anomalous financial flows irrespective of their size, may be preferred by intermediaries and other reporting entities required to monitor their customers' financial transactions and file suspicious transaction reports (STRs) accordingly under anti-money-laundering regulation; conversely, the value-based risk indicator could be more useful for law enforcement agencies mainly interested in allocating their resources and investigative efforts in those municipalities where cash flows of likely illegal nature are more sizable (Ardizzi et al., 2018).

### *5.2 Risk indicators and investigative results*[25]

This section and the following one attempt to provide a validation of the money-laundering risk indicators defined above, through two different and complementary approaches, that is, respectively, (i) the (qualitative) comparison with investigative evidence and (ii) statistical tests based on independent measures of crimes and money laundering.

As a first approach, with the help a major Italian law enforcement agency (ROS, *Carabinieri*) we compare the territorial pattern of our indicators against the information on investigative activities related to Italy's mafia-style criminal organisations.[26] It turned out that the areas featuring the highest value-based risk of money laundering (Figure 2) broadly overlap with those where criminal organisations are documented to be more active.

This general finding holds both for the Southern provinces, directly controlled by the leading criminal syndicates, and for the richer Central and Northern regions, where the same criminal groups have been expanding their influence in the last decades by exploiting the opportunities offered by the increasingly lucrative market of illegal goods.

More specifically, from recent investigative actions on *'Ndrangheta* (the Calabria-based criminal syndicate) it emerged that such group is among the most powerful and dangerous criminal organisations worldwide, mainly as a result of its business-like resourcefulness and its primacy in international drugs trafficking. Its marked attitude to expand its influence also abroad and its significant corruptive power have turned it into a dynamic and ruthless financial holding. As a matter of facts, most Calabria's provinces feature a significant money laundering risk according to our value-based risk indicators.

More in detail, several investigations showed that *'Ndrangheta*'s franchises have been successfully established in the North-Western regions of Lombardy, Piedmont and Liguria (all hosting high and medium-high risk provinces according to our indicators) by reproducing the criminal behaviour and organisational structure typically adopted in the region of origin and following the practice which is typically referred to as "criminal colonization". The central role played by *'Ndrangheta* in other Central and Northern areas of Italy was confirmed by important enforcement actions carried out in some provinces of Umbria and Emilia-Romagna concerning offshoots of clans originating in Crotone province. Our indicators show that a few provinces in Emilia-Romagna and Umbria feature a particularly high money laundering risk.

In all cases, the primary aim *'Ndrangheta* pursued in "exporting" its criminal activity was that of reinvesting unlawful proceeds (mainly from drug trafficking) into the legal economy and infiltrating local political institutions.

Drug trafficking, extortions and usury are the main sources of *Camorra*'s illegal proceeds, which is mainly active in the Southern region of Campania (where Naples, Caserta and Salerno provinces are all

[25] This section received a key contribution from Major Gaetano Licari, Department Analysis of *Raggruppamento Operativo Speciale* (Carabinieri).

[26] The ROS Department of *Carabinieri* gathers qualitative information from all major investigative activities – including those carried out by other police forces – on verified misconducts committed by leading criminal organisation.

marked by high risk). Clans also operate and influence business activities outside the region by participating directly into public and private procurements and by laundering vast amounts of ill-gotten funds.

The *Casalesi's* clan – characterized by a hierarchical structure more akin to those of the Calabrian and Sicilian mafia – has extended its activities from the original province of Caserta to Emilia- Romagna. Well documented money laundering operations in this area involved the purchase of real estate and commercial activities. The same type of illicit activities have been carried out by the offshoots of other *Camorra* clans in the Central regions of Lazio and Tuscany, both featuring several high and medium-high money laundering risk provinces.

*Cosa Nostra* typically exerts a deeply-rooted and pervasive territorial control in its native Sicily, where is mainly involved in extortion. Accordingly, it persistently holds sway on the local public and private investment, also thanks to its good connections with the administrative institutions. In this regard, the areas featuring the highest criminal infiltration are the provinces of Palermo and Catania (which are the sole Sicilian provinces with high money laundering risk), because they host a significant share of Sicilian business activities connected to *Cosa Nostra*'s local offshoots.

Outside Sicily, *Cosa Nostra* has been long operating in areas where, although without the favourable conditions enjoyed in the territories of origin, it effectively succeeds in infiltrating local economic activities for the reinvestment of its illicit resources. In the regional territories of Lazio, Lombardy, Piedmont and Friuli-Venezia Giulia (here Udine is the only high-risk province in our map), *Cosa Nostra* usually eschews its traditional operations, but relies on local fiduciaries who act as a reference for the whole organisation, whilst the control of basic criminal activities is left to local groups.

Apulia's organised crime – known as *Sacra Corona Unita* – is made up of heterogeneous clans, locally involved in extortion, usury and drug trafficking (especially with nearby Albania). Nevertheless, in some areas of the region such as the provinces of Foggia, Lecce and Brindisi (all but the latter with significant money laundering risk), single groups typically implement common criminal strategies for obtaining economic returns and infiltrating legal businesses, mainly in the procurement sector and the provision of security services.

Finally, it is worth stressing that all the main criminal groups of the country have established their operations also in Rome and its province (high risk in the map), either by means of single individuals or local offshoots, mainly dealing in drug trafficking, money laundering and the reinvestments in legal businesses.

### *5.3 Empirical validation of the indicators*

In order to further validate our results, we analyse the correlation between our risk indicators and several local indicators of crime diffusion and money laundering.

As previously explained, we intentionally chose not to include such variables in the model specification for a variety of reasons. Local indicators on crime suffer from heterogeneous under-reporting of victims and uneven police enforcement effectiveness that may imply a significant bias in official crime statistics. For similar reasons we avoid using STRs statistics as a proxy of money laundering, since they may simply represent a measure of anti-money laundering detection effectiveness and suffer from a heterogenous banks' propensity to report.[27] Moreover, and above all, deriving the risk indicators from a model which includes local measures of crimes and STRs would imply *constraining* such risk indicators to be *exactly proportional* to such measures (the proportional factor being the estimated regression coefficients), and therefore would convey no value added or information gain with respect to looking at the territorial distribution of the crime and STR data themselves[28].

[27] See Gara and Pauselli (2016).

[28] On a larger scale, some studies provide evidence that a greater risk of money laundering does not fully reflect the level of crimes within a country but its degree of economic/financial 'attractiveness' (see ECOLEF, 2013; Eurostat, 2018; Gara et al., 2018).

As a consequence, we have chosen to leave crime reports and STRs out of the model and have introduced them only at this stage of the analysis, by measuring their correlation with our risk indicators as a way to validate our results (precisely, in order to rely on more accurate proxies of money laundering, we use the number of individual suspicious transactions rather than the number of STRs).[29] The main results are the following.

Firstly, Table 4 reports the Pearson correlation coefficients between our value-based risk indicator (i.e. that depicted in Figure 2) and the number of suspicious transactions and crime reports observed, respectively, at bank-municipality and municipality level. With regard to suspicious transactions, we distinguish for (i) the risk score of the respective STR[30], and (ii) the type of suspicious transactions (cash vs. non-cash). As for the crimes considered, they are those that are usually referred to in the literature as *power syndicate crimes* (extortion and mafia-style conspiracy) and *enterprise syndicate crimes* (drug dealing, prostitution and money laundering).

**Table 4**
**Pearson correlation between the (value-based) money laundering risk indicator and a) suspicious transactions and b) criminal reports**

| | Bank-municipality level | Municipality level |
|---|---|---|
| *a) Suspicious transactions* | | |
| *From all STRs:* | | |
| all transactions | 0.240*** | 0.773*** |
| cash transactions | 0.157*** | 0.731*** |
| *From high-risk STRs:* | | |
| all transactions | 0.208*** | 0.728*** |
| cash transactions | 0.139*** | 0.636*** |
| *b) Crime reports* | | |
| All crimes | - | 0.898*** |
| Extortion | - | 0.864*** |
| Mafia-style conspiracy | - | 0.183*** |
| Money laundering | - | 0.547*** |
| Drug dealing | - | 0.893*** |
| Prostitution | - | 0.795*** |
| *N observations* | 29,226 | 7,440 |

Note: the (value-based) money laundering risk indicators are measured as the sum, at municipality or bank-municipality level, of the estimated anomalous cash inflows (see equation [3]).
p-value: *** <0.01, ** <0.05, * <0.1.
Source: UIF for STR data; the Italian law enforcement agencies' centralized database SDI for data on crime reports. Data refer to 2015.

The outcome confirms a general positive and significant correlation of our risk indicator with all the measures of money laundering and criminal activity, across all the crimes examined and irrespective of the type of financial transaction considered.[31] In this respect, the empirical evidence that we obtain (specifically the municipality level figures) suggests that cash anomalous flows are a useful red flag

[29] Each STR typically includes several suspicious transactions which can be of different type (cash and non-cash) and may take place in different locations. We thus extracted, for each STR, data on the individual transactions reported.
[30] Each STR received by UIF is associated to a specific risk score which measures the relevance of the report for anti-money-laundering purposes (risk scores range from 1 to 5). The score is first assigned by an automatic algorithm based on several factors (such as the amount of funds involved and the connection with previous cases or ongoing investigations); it can be subsequently adjusted by UIF analysts according to what emerges from their financial investigations.
[31] For robustness checks we also computed Spearman (rank) correlation indices and obtained results consistent with those shown in Table 4.

indicator for identifying geographical areas possibly featuring more intensive money laundering (not necessarily limited to cash transactions or petty money laundering) or criminal activities at large.

The robustness of such results was confirmed through tests of mean comparison; the results are reported in Table 5 for each money laundering and crime proxy, respectively for bank-municipality pairs and for municipalities.[32] They clearly show that the per capita numbers of suspicious transactions and of crime reports are, in all cases with the partial exception of mafia-style conspiracy, significantly higher in 'risky' bank-municipalities and municipalities.

**Table 5**
**Comparison of means, at bank-municipality and municipality level**
(all variables are normalised by municipality population)

| | Bank-municipalities | | | Municipalities | | |
|---|---|---|---|---|---|---|
| | *Means* | | *Difference significance* | *Means* | | *Difference significance* |
| | *Risky obs.* | *Non-risky obs.* | | *Risky obs.* | *Non-risky obs.* | |
| *a) Suspicious transactions* | | | | | | |
| *From all STRs:* | | | | | | |
| all transactions | 451.1 | 321.7 | *** | 2,909.9 | 1,208.7 | *** |
| cash transactions | 203.6 | 155.3 | ** | 1,286.6 | 586.1 | *** |
| *From high-risk STRs:* | | | | | | |
| all transactions | 284.9 | 193.9 | ** | 1,904.8 | 719.0 | *** |
| cash transactions | 116.7 | 92.8 | * | 744.6 | 347.9 | *** |
| *b) Crime reports* | | | | | | |
| All crimes | 99.0 | 54.2 | *** | 79.3 | 38.7 | *** |
| Extortion | 22.0 | 12.3 | *** | 16.7 | 8.8 | *** |
| Mafia-style conspiracy | 0.06 | 0.04 | | 0.08 | 0.02 | * |
| Money laundering | 3.5 | 2.1 | *** | 3.4 | 1.5 | *** |
| Drug dealing | 69.1 | 37.7 | *** | 56.2 | 27.0 | *** |
| Prostitution | 4.2 | 2.1 | *** | 3.0 | 1.4 | *** |
| *N observations* | 730 | 28,496 | | 356 | 7,084 | |

Note: The table reports results of two-sample *t*-test with unequal variances, $H_0$: *risky obs. mean =non-risky obs. mean.*
*Difference significance*: refuse of null-hypothesis ($H_0$), significant at $^{***}$ 0.01, $^{**}$ 0.05, $^{*}$ 0.10.
The number of suspicious transactions and crime reports is normalised to a population of 100,000.
Source: UIF for STR data; the Italian law enforcement agencies' centralized database SDI for data on crime reports. Data refer to 2015.

Finally, we deploy a multivariate correlation by estimating a logit regression model for the dummy dependent variable assuming value 1 in case of 'risky' municipality, defined as above, and 0 otherwise;[33] the covariates are all the money laundering and crime proxies already considered above.

[32] We first divided the sample of bank-municipalities between 'risky' and 'non-risky' ones, based on our money laundering risk indicator: namely, we identified as 'risky' the pairs belonging to the top 2.5% of the right-hand tail of the overall random effects distribution. We then computed, for each type of suspicious transactions and crime reports, the corresponding mean among, respectively, the 'risky' and the 'non-risky' bank-municipalities. Analogously, for municipalities, we identified as 'risky' those showing at least one bank-municipality anomaly; we then compared, for each type of suspicious transaction and criminal offence, the corresponding means across, respectively, the 'risky' and 'non-risky' municipalities.

[33] As to robustness, we performed the same regression at bank-municipality level, obtaining similar results for the crime variables, but lower statistical significance of the suspicious transactions coefficients.

**Table 6**
**Anomalies and municipality features (logit)**

| | *Dep. Variable = 1 if 'risky municipality', 0 otherwise* | | | | |
|---|---|---|---|---|---|
| | Logit 1 | Logit 2 | Logit 3 | Logit 4 | Logit 5 |
| *a) Suspicious transactions* | | | | | |
| *From all STRs:* | | | | | |
| all transactions | 2.8*** | | | | 2.7*** |
| cash transactions | | 4.7*** | | | |
| *From high-risk STRs:* | | | | | |
| all transactions | | | 2.8*** | | |
| cash transactions | | | | 3.8*** | |
| *b) Crime reports* | | | | | |
| All crimes | 275.2*** | 271.8*** | 277.4*** | 276.0*** | |
| Extortion | | | | | 956.2*** |
| Mafia-style conspiracy | | | | | 5317.2 |
| Money laundering | | | | | 535.2** |
| Drug dealing | | | | | 227.7*** |
| Prostitution | | | | | 118.4 |
| Constant | -3.2*** | -3.2*** | -3.2*** | -3.1*** | -3.2*** |
| *N observations* | 7,440 | 7,440 | 7,440 | 7,440 | 7,440 |
| AIC | 2,807 | 2,814 | 2,813 | 2,820 | 2,800 |
| BIC | 2,828 | 2,835 | 2,833 | 2,841 | 2,848 |

p-value: *** <0.01, ** <0.05, * <0.1; Inference based on the robust standard errors.
The number of suspicious transactions and crime reports is normalised by municipality population.
Source: UIF for STR data; the Italian law enforcement agencies' centralized database SDI for data on crime reports. Data refer to 2015.

Results are reported in Table 6. In the first four estimations the overall number of criminal reports is in turn associated, among the regressors, to each type of suspicious transactions: the respective regression coefficients are always positive and statistically significant.[34] A similar result is obtained disaggregating the number of crime reports by the type of offence (fifth column)[35].

## 6. Concluding remarks

The aim of this work is to construct risk indicators for detecting the potential surfacing of underground cash streams in Italian municipalities. This is done by setting up an econometric model based on data of cash deposits, which are detailed for 45,485 branches of Italian banks.

The empirical strategy involves the application of a *linear random effect* model: in this setting the response variable is regressed on observed covariates, whilst excluding some relevant unobserved regressors (in our case, cash-generating criminal activities). Data are grouped in homogeneous clusters (bank-municipality pairs), thus the extent to which the excluded covariates contribute to the unobserved heterogeneity can be measured by introducing cluster-specific effects, the so-called random effects.

Following a well–established strand of literature, our regressors include most structural determinants of cash holdings at municipal level, which are essentially a set of local economic and financial features: per capita personal taxable income, a measure of the propensity of banks' local clients

[34] We avoided including both the total number of crime reports and the separate figures for each type of offence simultaneously since they are highly correlated.
[35] In this regression, the coefficients for mafia-style conspiracy and prostitution are still positive although statistically not significant.

to use means of payment alternative to cash, proxies of the easiness to access financial services, dummies accounting for the geographical location of each municipality and for the type of bank involved. Since we aim to focus on cash flows emerging from ‘strictly criminal’ activities, we include an additional covariate controlling for the size of the underground economy.

Given our empirical strategy, the random effects the model estimates capture the systematic contribution to the variability of our dependent variable (the use of cash, normalized to non-cash payments) produced by all unobserved determinants (possibly criminal and money laundering activities), net of the erratic component. These we take as our risk indicators for anomalous cash usage.

The estimates of our benchmark model prove to be robust to different specifications and the emerging coefficients of all covariates are consistent with the expected correlations, as suggested by the literature. This we consider as a prove that the underlying model is well specified and estimates are correct, hence our indicators can be confidently relied upon for risk measurement.

It is worth stressing that the goal we pursue is not that of identifying single anomalous cash transactions, but to measure the local cash use that may be associated to (and generated by) illegal activities; accordingly, we are able to produce heat maps of anomalous cash deposits and a list of riskier municipalities and provinces in terms of anomalous use of cash.

Quite interestingly, supporting evidence on the reliability of such indicators is provided by investigative evidence, which is found to be consistent with the maps of risk based on the results of our model. A specific contribution to this study from a major Italian law enforcement agency (*ROS – Carabinieri*) shows that most of the riskier provinces emerging from our econometric analysis broadly overlap with those areas where criminal organisations are deeply rooted or operate on a routine basis, according to investigative results and judiciary evidence.

In order to validate and characterise our indicators further, we analyse their correlation with some indicators of local crime diffusion or suspected money laundering activity. Regardless of the approach adopted (univariate correlation, mean comparison, multivariate analysis), a positive and significant correlation emerges between our risk indicators and all the measures and reports of illegal conducts, irrespective of the type of suspicious financial transactions (cash-only or otherwise) or the type of criminal activity considered.

Overall, our methodology seems to be particularly appropriate for the construction of risk indicators that may be deployed to various operational ends: i) reporting entities may refer to the *incidence-based risk indicator* in order to monitor more effectively their clients’ financial transactions at local level to the end of filing more reliable and significant suspicious transaction reports to the FIU; ii) likewise, by relying on the *value-based risk indicator* law enforcement agencies can concentrate their efforts in the areas where they are more likely to uncover conspicuous illegal proceeds; iii) the FIU itself can use these indicators, together with additional intelligence, to direct its own off-site and on-site checks and analyses.

## References


Ardizzi G., C. Petraglia, M. Piacenza, F. Schneider and G. Turati (2014), "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.

Ardizzi G., P. De Franceschis and M. Giammatteo (2018), "Cash payment anomalies: An econometric analysis of Italian municipalities". *International Review of Law and Economics*, 56, pp. 105-121.

Bell A. and K. Jones (2015), "Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data." *Political Science Research and Methods*, 3(1), pp. 133-153.

BIS – Bank of International Settlements "Statistics on payment, clearing and settlement systems in the selected countries", various issues.

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

Capgemini and BNP Paribas (2016), "World Payments Report, 2016".

Esselink H. and L. Hernández (2017), "The Use of Cash by Households in the Euro Area". *ECB Occasional Paper* No. 201.

Europol (2015), "Why is cash still king? A strategic report on the use of cash by criminal groups as a facilitator for money laundering," Europol, The Hague, Netherlands.

EUROSTAT (2018), "Handbook on the compilation of statistics on illegal economic activities in national accounts and balance of payments", *Manuals and Guidelines*, Luxembourg.

Financial Action Task Force (2015), "Money laundering through the physical transportation of cash," FATF Paris, France and MENAFATF, Manama, Bahrain.

Financial Action Task Force (2016), "Anti-money laundering and counter-terrorist financing measures (Italy)" Fourth Round Mutual Evaluation Report, FATF, Paris.

Gara M. and C. Pauselli (2016), "Looking at 'Crying wolf' from a different perspective: An attempt at detecting banks under- and over-reporting suspicious transactions". UIF, *Quaderni dell'antiriciclaggio, Collana Analisi e Studi*, n. 4.

Gara M., M. Giammatteo and E. Tosti (2018), "Magic mirror in my hand… How trade mirror statistics can help us to detect illegal financial flows". UIF, *Quaderni dell'antiriciclaggio, Collana Analisi e Studi*, n. 10.

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

ISTAT (2017), "L'economia non osservata nei conti nazional", *Statistiche report*, Rome. https://www.istat.it/it/archivio/204357.

Mundlak Y. (1978), "Pooling of Time-series and Cross-section Data." *Econometrica*, 46(1), pp. 69-85.

Project 'ECOLEF' (2013), "The economic and legal effectiveness of anti-money laundering and combating terrorist financing policy", Final report, Utrecht University. http://www2.econ.uu.nl/users/unger/ecolef_files/Final%20ECOLEF%20report%20(digital%20version).pdf.

Rogoff K. S. (2016), "The Curse of Cash." Princeton University Press, New Jersey.

Rabe-Hesketh S. and A. Skrondal (2012), "Multilevel and Longitudinal Modeling Using Stata" (Third Edition), Volume I: Continuous Responses. College Station, TX: Stata Press.

Skrondal A. and S. Rabe-Hesketh (2004), "Generalized Latent Variable Modeling: Multilevel, Longitudinal and Structural Equation Models." Boca Raton: Chapman and Hall.

Stix, H. (2004), "How Do Debit Cards Affect Cash Demand? Survey Data Evidence." *Empirica*, 31(2-3), pp. 93-115.

Unità d'Informazione Finanziaria (2016), "Annual Report".