Vulnerability to Money Laundering and Deterrence: Evidence from Italy

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Abstract

This paper analyzes the vulnerability of the legal sector to money laundering at local level. Assuming that criminals are rational investors who account for risks and returns of both legal and illegal investments, we define vulnerability as a function of well identified drivers. Proxies of these latter ones are used to empirically investigate the relationship between institutional/economic factors and vulnerability of Italian provinces in the period 2008-2013. Exploiting instrumental variable techniques, we focus on the impact of suspicious transaction reporting to the Financial Intelligence Unit. Results highlight positive effects of crime prevention policies and activities of suspicious transaction reporting, particularly. Further dimensions of local vulnerability are outlined: the *unmeasurable heterogeneity across provinces* shows that some areas are systematically more vulnerable because of persistent local features that cannot be specifically identified; the *idiosyncratic vulnerabilit*y pinpoints that some provinces have been occasionally subject to abnormally intense money laundering activity.

Keywords: money laundering, vulnerability, suspicious transaction reporting.

JEL Classification: K14, K20, K42

Introduction

It is long recognized that criminals, especially organized crime, not only operate on illegal markets by producing and supplying illegal goods (i.e. drug trafficking, human trafficking and smuggling, prostitution, counterfeiting, etc.), but also operate on legal markets and infiltrate legal economies. The main driver of criminal infiltration in the legal sector is money laundering, a crime itself. The presence of criminal activities in a given area is usually recognized as a negative externality that can significantly depress local legal economy (Asmundo and Lisciandra 2008, Costa 2011, Labsdorff 2002, Shelling 1967 and 1971). However, criminal infiltration in legal activities may even represent a more dangerous phenomenon since it can seriously threaten the physiology of a safe legal economy (Burdet et al. 2003, Cook 1986, Di Nicola 2006, Kelly 2000, Coniglio et al. 2010, Daniele and Marani, 2006, Pinotti 2010, Van Dijk, 2007).

The assessment of the presence and the extent of criminal activities in the illegal sector is a challenging issue given the intrinsically elusive and concealed nature of criminal behavior. Typically, statistics concerning suspected, investigated, or prosecuted crimes only grasp the tip of the iceberg (Cornwell and Trumbull 1994, Dalla Pellegrina 2008, Trumbull 1989, Saffer and Chaloupka 1999, Marselli and Vannini 1997). Measuring criminal infiltration in the legal economy is even a more serious problem since the legal nature of the *polluted* activities makes detection extremely difficult (Benson et al. 1994, Carr-Hill and Stern 1973, Cherry and List 2002, dalla Pellegrina et al. 2005). Certainly, data and statistics concerning (detected) money laundering provide useful information (Masciandaro 1998, 1999, 2000a and 2000b). However, the resulting picture remains incomplete (Benson and Zimmerman 2010, Cook, 1986).

The problem of evaluating the presence and the extent of criminal infiltration probably benefit from estimations and analyses of the *drivers* that can influence both the supply and the demand of illegal funds in both legal and illegal markets. From a conceptual perspective, to assess the *vulnerability* of a given area to criminal infiltration it is necessary to identify those local factors that can significantly drive criminal activities, on the one hand (illegal markets), and money laundering, on the other hand (legal markets).

The aim of this paper is to identify those institutional (i.e. detection, prosecution, etc.) and economic factors that are relevantly associated to crimes and money laundering (*institutional vulnerability*), and then provide a possible assessment of *unmeasurable heterogeneity* across provinces which makes some of them more vulnerable than others. Finally, we intend to retrieve a measure of *idiosyncratic vulnerability* which, on the one hand, cannot be directly grasped by usual measures of detected and prosecuted crimes and, on the other hand, does not systematically affect some specific provinces.

From a methodological perspective, it is worth noticing that criminal investors consider both legal and illegal markets when facing the decision to invest illegal funds. It is sound considering criminal investors as rational and well prepared individuals who take into account specific risks and returns that are associated to a given project when deciding their investment strategies. A direct consequence of criminal investment choices is the degree of penetration into legal and illegal local sectors. Therefore, the analysis should carefully distinguish specific features characterizing local projects of investment both in terms of return and risk.

The purpose of the empirical analysis is to identify: a) factors that contribute to increasing *institutional vulnerability* of a given area to money laundering with special attention to the mechanism of reporting suspicious transactions to the Financial Intelligence Unit (FIU); b) *local heterogeneities* that are significantly associated to money laundering; and finally, c) areas that are *idiosyncratically affected by criminal infiltration*.

The paper is organized as follows. Section 2 presents a simple theoretical model to describe the decision of a criminal investor who has to allocate an illegal capital; Section 3 presents the empirical analysis. Section 4 concludes and discusses policy implications. Details of the model and additional tables are presented in the Appendix.

2. The model

To frame the empirical analysis of Section 3 we outline a simple theoretical framework: it sketches how main economic and institutional factors affecting investment choices can influence local vulnerability. [1]

2.1. Hypothesis

We consider a risk neutral investor who has an initial capital K_0 that has been illegally generated in the past. The investor's problem is to decide his/her optimal investment strategy according to a multi-period scheme that is illustrated in Figure 1:

<u>At time 0</u>, the investor decides how to allocate K_0 between a legal project and an illegal one. We name a_0 the capital share that is invested in the legal activity while the remaining share (1- a_0) is allocated to the illegal activity (crime).

It is worth noticing that the legal investment at t=0 in fact implies money laundering. Given the illicit origin of K_0, the investment in a legal asset (i.e. real estate investment, purchase/establishment of firms/company shares, purchase of capital goods and factors of production) practically corresponds to a process of transforming the proceeds of crime into ostensibly legitimate money/assets - as to say money laundering.

[1] Here we generalized the intuition originally proposed in Masciandaro (2001), Cifarelli et al. (2002) and Masciandaro (2002) to analyze the optimal investment choices when alternative (legal and illegal) financing policies are available.

On the other hand, the illegal activity is some sort of source-crime that can produce a monetary return (i.e. drug trafficking, human trafficking and smuggling, prostitution, counterfeiting, etc.). For the sake of simplicity, we assume that the illegal investment is carried out using only dirty money; however, we can remove this assumption without loss of generality.

<u>At time 1</u>, if the underlying illicit activity (money laundering or source-crime) is not detected, the investment generates a return[2] that is re-invested for a further period.

- The legal investment is assumed to be highly asset-specific so that the return from the legal activity is automatically reinvested in the same activity. This assumption is related to the fact that the legal investment implies money laundering: any switch from the legal to the illegal sector - and vice versa - involves a higher probability of detection of illegal activities. Indeed, the same regulation is applied to identify both the flows between illegal and legal markets – as it is the case, for example, for drug trafficking – and the flows between legal and illegal activities – as, for example, in the case of terrorism financing. Define i_A as the return rate of the legal activity. This rate can even be near the zero lower bound, considering that money laundering can be extremely costly.

- Define i_C as the return rate of the illegal activity. Contrary to the legal return, the return from the illegal activity can be, once again, split between the legal activity (share a_1) and the illegal activity.

If the underlying illicit activity (money laundering or source-crime) is detected, the criminal investor is punished with a sanction depending on the severity of the illicit behavior. Obviously, specific risks of detection must be considered. We assume that, after one period within the legal economy, illegal proceeds are "clean" and money laundering cannot be detected anymore. Conversely, source-crime can be detected and punished at each period.

- Define p_A as the probability of detection for money laundering associated to the legal investment and p_C as the probability of detection for the source-crime. Note that the first time an illegal amount infiltrates in the legal economy there is a certain risk of being detected and punished for money laundering.

- In the case of detection, the illicit behavior is punished with a sanction $S(I_t)$ that is assumed to be increasing in the severity of misbehavior that, in turn, is measured by the funds invested in the activity I_t ($dS/dI_\cdot>0$). For the sake of simplicity, we assume that the sanction corresponds to the invested amount squared $S = (I_t)^2$. This assumption can be justified by noticing that, on the one hand, the invested amount is confiscated, on the other hand, both money laundering and typical source-crimes imply high criminal sanctions, including conviction.

[2] Consumption may be considered as a form of unproductive investment.

At time 2, if the possible underlying illicit activity is not detected, investments generate returns, otherwise the illicit activity is punished. Finally, time ends. The latter assumption helps making tractable the present analysis without loss of generality.

Define r as the relevant discount rate.

2.2. How investment determinants affect vulnerability to criminal infiltrations

Proceeding backward, the criminal investor at time 1 sets his/her optimal share a_1 by

$$\max_{a_1} \Pi_1$$

where

$$\Pi_1 = (1 - p_A)a_1(1\text{-}a_0)K_0(1+i_C)(1+i_A) - p_A(a_1(1\text{-}a_0)K_0(1+i_C))^2 + (1\text{-}p_C)(1\text{-}a_1)(1\text{-}a_0)K_0(1+i_C)^2 - p_C((1\text{-}a_1)(1\text{-}a_0)K_0(1+i_C))^2$$

Note that the first term of the sum which is defined above is the expected return resulting from the re-investment in the legal activity of a share a_1 of the capitalized illegal investment at the end of t=1 when money laundering is not detected. The second term is instead the expected punishment if money laundering is detected. The third term is the expected return resulting from the re-investment in the illegal activity of a share 1-a_1 of the capitalized illegal investment at the end of t=1 when the source-crime is not detected. The fourth term is instead the expected punishment if the crime is detected.

The resulting $a_1^*(a_0, p_A, p_C, i_A, i_C, K_0)$ is a reaction function that depends on a_0 which is our main variable of interest since it can be considered as a measure of vulnerability of the legal sector to criminal infiltration given that the criminal faces a multi-period investment decision.

Now, the criminal defines his/her optimal share a_0 by

$$\max_{a_0} \Pi_0 \tag{2.1}$$

where

$$\Pi_0 = \frac{1-p_A}{1+r} a_0 K_0 (1+i_A)^2 - \left[p_A(a_0 K_0)^2 + p_C((1\text{-}a_0)K_0)^2\right] +$$
$$+ \frac{1-p_C}{1+r}\left[(1-p_A)a_1^*(1\text{-}a_0)K_0(1+i_C)(1+i_A) - p_A\left(a_1^*(1\text{-}a_0)K_0(1+i_C)\right)^2 + (1\text{-}p_C)\left(1\text{-}a_1^*\right)(1\text{-}a_0)K_0(1+i_C)^2 - p_C\left(\left(1\text{-}a_1^*\right)(1\text{-}a_0)K_0(1+i_C)\right)^2\right]$$

Note that the first term of the sum which is defined above is the present value of the expected return resulting from investing a share a_0 of the initial capital for two periods in the legal activity when money laundering is not detected. The second term is the expected punishment in the first period.

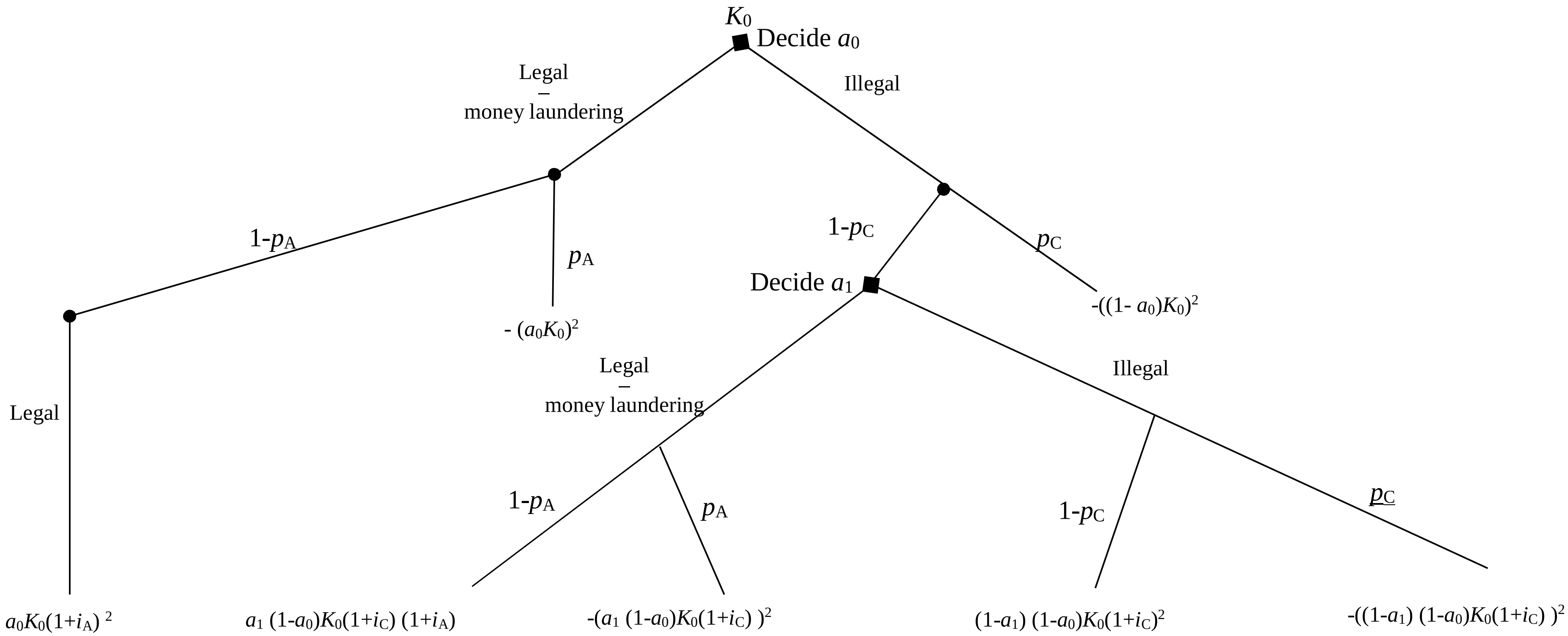


Figure 1. Investment scheme

The third term is the present value of the expected return resulting from the re-investment of share $a_1^*(a_0,.)$.

By solving the optimization problem described in (2.1) we obtain two solutions. However, model calibration[3] allows selecting one admissible solution corresponding to the functional form of $a_0^*(p_A, p_C, i_A, i_C, r, K_0)$. Details are provided in Appendix 1.

The optimal share a_0^* can be interpreted as a measure of vulnerability to criminal infiltration of the legal sector since it corresponds to the share of capital of illegal origin that infiltrates the legal economy though money laundering when criminals face a multi-period horizon.

By inspecting $a_0^*(.)$ we conclude the following:

$$\begin{aligned} &\partial a_0^* / \partial p_A < 0, \quad \partial a_0^* / \partial p_C > 0, \\ &\partial a_0^* / \partial i_A \geq 0, \quad \partial a_0^* / \partial i_C \gtrless 0 \\ &\partial a_0^* / \partial r \leq 0, \quad \partial a_0^* / \partial K_0 \gtrless 0 \end{aligned} \tag{2.2}$$

(2.2) shows the impact of institutional factors (probabilities of detection, and implicitly, sanctions) and economic factors (return and discount rates and initial capital) on the optimal decision of investment corresponding to our measure of vulnerability.

The institutional factors seem to affect the vulnerability as expected. A greater effort in detecting and then punishing money laundering results in a minor vulnerability to infiltration of the legal sector. Conversely a higher probability of detection of source-crime makes investment in the legal sector more appealing (Figure A.1 and A.2 in Appendix 1). From this perspective, the relation of substitution between legal and illegal sectors emerges clearly.

Concerning the economic factors, a higher legal investment return is associated to a major vulnerability since legal activities represent a good opportunity of investment (Figure A.3). Conversely, vulnerability of the legal sector is decreasing in the discount rate (Figure A.5).

The role of the illegal return rate and the initial capital is uncertain and depends on the parameters of the model. In this respect, it is worth noticing that, source-crime and money laundering (here the legal investment) might be seen both as complements (source-crime feeds money laundering) and as substitutes (money laundering is an investment alternative to crime). The uncertain sign of both the first derivative of

[3] We calibrated the model by setting variables at the average levels of the variables that we used in the empirical model (see Table 1 and Appendix 1).

a_0^* with respect to i_C and the first derivative of a_0^* with respect to K_0 seems to capture this mixed nature of complementarity and substitution. When $\partial a_0^* / \partial i_C < 0$, the dimension of substitution prevails. Conversely, when $\partial a_0^* / \partial i_C > 0$ complementarity emerges between illegal investment and money laundering. Once the model is calibrated with parameter values corresponding to the average of the variables that have been selected to carry out the empirical analysis, complementarity would seem to prevail (see Figure A.4).

Parameter calibration also allows concluding that vulnerability is expected to be decreasing in the initial capital (see Figure A.6). This is consistent with the idea that the penetrating the legal sector represents a decreasing returns-to-scale opportunity for criminals.

The next empirical section aims at analysing the impact of institutional and economic factors on the vulnerability to criminal infiltration of the legal sector of Italian provinces.

3. Empirical analysis

The purpose of the empirical analysis is threefold. First, we want to test the predictions of the model illustrated in the previous section with the aim of isolating the individual contribution of some actions of crime prevention on the vulnerability of Italian provinces to money laundering (*institutional vulnerability*). Policy provisions consisting intensifying “law and order” activities should follow from this stage.

Second, the analysis is intended to identify *unobserved heterogeneity* across provinces, that is local characteristics which are not individually measurable, which embed some incentives or restraints to embark on money laundering activities. Such phenomena are mostly related to time-persistent institutional factors which are proper of a given geographical area, in our case coinciding with the province. Some examples are the efficiency of local administrations, local corruption, clusters of population specialized in some criminal activities, the presence of different levels of social capital, a social environment favoring money laundering, etc. This should provide suggestions in terms of conveying crime prevention activities and “educational activities” aimed at improving social, cultural, and systemic antibodies against money laundering.

Third, we seek to pinpoint the geographical areas that have been occasionally subject to “abnormally” intense money laundering activity (*idiosyncratic vulnerability*). This is particularly relevant for preventing this crime in correspondence of similar events that might further take place elsewhere in the country.

We have information about law reporting and proxies of other variables included in the model which allow us to quantify the extent of their contribution to money laundering. However, we cannot observe directly neither the true incidence of money laundering nor that of other (source-) crimes because of their hidden nature. Criminal activities are indeed part of the underground economy and, as we mentioned earlier, law reports (*denunce*) can grasp only a share of the overall phenomenon. Furthermore, a relatively high number of reports in a given province may provide contrasting indications. On the one hand, their increase may lead to infer that the latent phenomenon (actual incidence of crime) has also increased. On the other hand, more law reports could also suggest that either the authorities have become more efficient in detecting illegal behaviors, or citizens have become more willing to report other people's misconducts.

Such difficulties are common to all empirical contributions dealing with underground phenomena and, to our knowledge, it has not so far been disentangled by any earlier study. To cope with this problem, we rely on two main assumptions. The first is that the number of law reports is positively correlated with the latent fact (actual crime intensity). According to the discussion above, this is reasonable to the extent that there is available information regarding the ability of the law enforcement authorities in preventing criminal activities so as to exclude that an increasing number of reports reflects more efficient crime repression. The second assumption is that the share of law reports on the actual dimension of money laundering in a given area is not dissimilar from the share of law reports for source-crimes on their actual dimension (i.e. the degree of hidden phenomenon is similar for the two types of crime). If this assumption holds, the ratio of law reports for money laundering to law reports for source-crimes can indeed represent a fair measure of criminal infiltration in the legal economy.

According to the model illustrated in Section 2, for each province we collected information regarding the law reports and the probability of detection and prosecution of both money laundering and source-crimes, the discount rate on investment in legal and illegal activities, and proxies for the return on legal investments.[4] In addition, we have information on the number of *suspicious transactions* transmitted to the FIU by financial intermediaries and other professionals (signaling bodies).[5] This variable represents the focus of this analysis because, since the risk based approach has been introduced in 2007 – and actually implemented in 2009 with the establishment of the mechanism of reporting suspicious transactions – the issue regarding its effectiveness has not yet been rigorously addressed in the literature.

The problem of interpreting the causal effects of changes in the number of suspicious transactions on local vulnerability to money laundering (money laundering/source-crimes) is like the one discussed above with regards to law reports. Going back to that argument, a plausible proxy of local vulnerability relies on the

[4] Further developments of the research aim at including a measure of social capital to account for the return on illegal investment. The idea is that a high level of social capital in a given geographical area should make crime less worthy due to a lower demand for illicit activities from citizens living in that area.

[5] The FIU is an autonomous body incorporated into the Bank of Italy since the Legislative Bill No. 231/2007 was enacted as an implementation of the Directive on the prevention of money laundering and terrorism financing (see dalla Pellegrina and Masciandaro 2009 for details).

observable incidence of crimes, and again the reliability on law reports as a proxy for the actual incidence of crimes raises some worthwhile issues.

On the one hand, an increasing number of suspicious transactions conveyed towards the FIU in relation to some specific geographical area should in principle reduce the share of laundered funds the spirit of deterrence, given the stock of source-crimes committed in that area. In this vein, criminals would interpret an intensified number of suspicious transactions as a mechanism that harshens the reprehension activity on money laundering.[6] A measure of vulnerability based on law reports for money laundering to total source-crimes would eventually indicate that the area under investigation is less vulnerable.

On the other hand, much depends on how both criminals and the enforcement authorities react to the information content of a change in the signaling mechanism. If an intensified signal enhances the reprehension activity, whereas criminals do not change their attitude in terms of both money laundering and source-crimes committed, the number of law reports for money laundering increases given the stock of source-crimes. This would artificially increase local vulnerability although this would be a pure outcome of an improvement in the efficiency of the detection mechanism based on the system of suspicious transactions. Conversely, more reports of suspicious transactions per source-crime may as well represent a confounding factor, bringing efficiencies to the investigative apparatus. In this situation, a higher number of suspicious operations transmitted to the FIU would imply less law reports, thus misleadingly lowering our measure of vulnerability.

It is worth noticing that in this discussion we separately treated the reaction of criminals and authorities to an increase in the number reported suspicious transactions. However, any unmeasurable event affecting the willingness to undertake money laundering may result in a combined response which could affect both the volume of law reports and reported suspicious transactions in any direction, with a net impact which is in principle indeterminate. For instance, if for some unknown reason it becomes more profitable to undertake money laundering in a given area, we might observe a contemporaneous increase of both reported suspicious operations and law reports for money laundering. However, this spurious evidence would not be indicative of the fact that there is a positive causal link between signaling and law reports (and eventually vulnerability to money laundering). This calls for a careful management and a wary interpretation of the results of the empirical analysis. To avoid such misleading warnings and address a causal response, we ought to find some elements that impact on the signaling mechanisms without being related to unmeasurable determinants of the volume of law reports.

[6] In addition, a fact which is not contemplated in the previous section, dirty money accruing from elsewhere to be washed in that area could also be curtailed.

The first step towards curbing these possible sources of bias is to make use of variables that are related to widely recognized tools exploited by criminal organizations to carry out money laundering operations. In the specific, we account for the volumes of cash accruing to the banking system (and ultimately to the Central Bank), the stock of bank deposits, and the number of real estate transactions in each province.[7] An aggregate increase in these variables, given the economic dimension of the geographical areas under investigation, should be indicative of an increase in the money laundering activity and therefore intensify both the volume of suspicious operations and the number of law reports.

However, *anomalies* in these variables (such as for example their higher volatility) may instead alter the signaling activity to the FIU without *directly* impacting on law reports. For example, it is reasonable to suspect that more instability of cash transactions, leaving their aggregate volume unaffected, might represent a confounding factor for financial intermediaries. The latter, fearing of missing some relevant indication for the FIU, increase the volume of *suspicious* operations transmitted. At the end, more suspicious operations are conveyed per crime committed. This helps identifying the causal effect of changes in the volume of reported suspicious operations on law reports for money laundering. Then, whether vulnerability is driven up or down is a matter of the combined reaction of both criminals and the reprehension authorities, as extensively discussed above.

3.1 Dataset

Data have been drawn from the Italian National Institute of Statistics, the Bank of Italy, and Guardia di Finanza. We concentrate on the period 2008-2013, for which data on suspicious transactions are available. Information is either quarterly, biannually, or annually available, depending on the series. We chose to set observations on a quarterly basis, interpolating biannual and annual series where needed.

Table 1 reports the summary statistics of the main variables used to perform the empirical investigation for the entire period of analysis. We provide information on means, standard errors, min and max, either on the absolute value of the variables and on some ratios which are used to perform the analysis.

As for source-crimes, previous studies have estimated that the highest yielding activities for the organized crime are drug trafficking, prostitution, racketeering, and counterfeiting. It has been assessed, for example, that drug trafficking is the most profitable crime with an estimated turnover of a 7.7 billion euro, whereas prostitution and counterfeiting have an estimated turnover of 4.6 and 4.5 billion euro respectively (−, annual report 2013). According to this information, we use the total number of reported crimes for drug trafficking, prostitution, racketeering, counterfeit goods, robberies and frauds as a proxy of the capital that has been

[7] According to the FIU (biannual reports, various editions) most part of the signaling bodies is represented by financial intermediaries and notaries.
https://uif.bancaditalia.it/pubblicazioni/quaderni/2009/boll-sem-2009-1/Bollettino_semestrale_I_sem_2009.pdf

illegally generated by source-crimes (K_t in the model). The average number (by province) of law reports for these crimes in the period of analysis is 1,863 on an annual basis, with a minimum of 21 cases in the small province of Vibo Valentia in the first quarter of 2009 (referred to the period 1/4/2008 to 31/3/2009) and a maximum of 23,060 in the province of Naples throughout year 2011. Law reports for money laundering are in much lower proportion compared to source-crimes (14 per year on average, with a peak of 165 in the province of Naples in 2012).

We employ the annual interest rate paid on deposits (on ordinary bank customers, according to the definition of the Bank of Italy) as a proxy of the discount rate (r in the model). This series is available only at a regional level. Its minimum level (0.18%) is recorded in Calabria the period 1/7/2009 to 30/6/2010 whereas the maximum level is observed in Lazio throughout year 2011 (1.09%).

To account for the return on legal investments (i_B in the model) we use the ratio of GDP at the provincial level to total bank loans. The GDP is on average 13,834 mil. euro on an annual basis, the highest level is recorded in Milano at the end of 2011 (167,592 mil. euro). Average bank loans are 16,425 mil. euro with a peak of 560,072 mil. euro in the province of Milano at the end of 2013.

As for the instruments through which money laundering takes place bank deposits exhibit the same pattern of loans (8,811 mil. euro on average with a variance of 20,756). Also for this variable the highest value is observed in Milano at the end of year 2013. Cash accruing to the Bank of Italy are in the amount of 844 mil. euro on average, with a maximum value recorded in Rome throughout year 2013 (8,925 mil. euro). Finally, the number of real estate transactions involving monetary payments is 9,300 on average, with a maximum of 89,005 in Milano in the period from 1/4/2008 to 31/3/2009.

Regarding the variables reflecting crime apprehension, we use the share of crimes with known authors [8] as a proxy of the efficiency of the investigation authorities in detecting illegal conducts. These are on average 59% and 69% for source-crimes and money laundering respectively (p_C and p_A). In particular, p_A has peaks of 88% in the province of Matera from 1/4/2008 to 31/3/2009 and 100% in some very small provinces (Aosta, Trento, Campobasso, Bolzano, and Isernia). Another variable related to crime deterrence is the length of criminal trials (see dalla Pellegrina, 2008). Trial duration is 332 days on average, the maximum length (598 days) is registered in Perugia at the end of 2013.

To define the local vulnerability to money laundering (a_t in the model) we computed the ratio of law reports for money laundering accrued to the FIU in the 12 months before the observation to the total number of law

[8] See dalla Pellegrina (2008a).

reports for source-crimes one quarter in advance.[9] The variable ranges from 0 (several small provinces) to 31% (Vibo Valentia from 1/7/2008 to 30/6/2009) and exhibits an average value of 0.8%.

Finally, we consider both province and time fixed-effects. The former are intended to capture time-invariant unobserved heterogeneity. Year dummies, instead, control for the consequences of the economic cycle and the evolution of the reporting mechanism to the FIU on crime rates.[10]

Table 1: Summary statistics – Italian provinces 2008-2013

	Variable	Unit	Mean	Std. Dev.	Min	Max
	ML suspicious transactions	nr.	407	822.970	0	7137
	GDP (Real, at 2010 price level)	Milion euro	13834.220	20882.980	1524	167592
r	Interest rate paid on deposits	Million euro	0.481	0.178	0.18	1.09
	Bank loans	Million euro	16424.980	49374.170	486	560072
	Bank deposits	Million euro	8811.302	20752.610	358	200582
	Cash accruing to Central Bank	Millions euro	844.187	1003.385	43	8925
	Real estate transactions	nr.	9300	10796.050	1031	89005
	ML law reports	nr.	14	24.785	0	165
K	Source crime law reports	nr.	1863	3107.790	21	23060
p_A	ML crimes with known author	% of tot. nr. of ML crimes	69	20.802	0	100
p_C	Source-crimes with known author	% of tot. nr. of source crimes	58.673	4.006	49	88
p_A, p_C	Length of criminal trials	days	332	99.576	126	598
a	ML law reports/Source crime law reports_1	%	0.808	1.297	0	30.588
i_A	Real GDP/Bank loans	Milion euro/Milion euro	1.398	0.594	0.298	3.608
p_A	ML suspicious transactions/ GDP Bil.	nr./Billion euro	27	24	0	226
	Bank deposits/ GDP	Milion euro/Milion euro	0.524	0.132	0.235	1.201
	Cash accruing to Central Bank/ GDP	Milion euro/Milion euro	0.070	0.024	0.026	0.154
	Real estate transactions/ GDP	nr./Milion euro	0.782	0.220	0.341	1.686

(a) Data are on a yearly basis. Obs. 2060. First column refers to the variables of the model in Section 2.

3.2 Methodology

We focus on the following (fully-comprehensive) equation: [11]

$$a_{i,t} = \beta_0 + \beta_1 r_{j,t} + \beta_2 i_{A\ i,t} + \beta_3 p_{A\ i,t} + \beta_4 ML\ devices_{i,t-1} + \beta_6 p_{C\ i,t-1} + \beta_7 K_{i,t-1} + \mu_i^a + \delta_t^a + e_{i,t}^a \tag{3.1}$$

[9] Lags are intended to capture the time needed to collect profits from illicit source activities and set up money laundering operations.

[10] See Figure A.1 in the appendix.

[11] According to the frequency of the data, *t* refers to quarters. As for stock measures (such as bank loans and deposits) and interest rates the variables report the balance at the end of each quarter, whereas for flow measures, like reports accrued to the Authorities the variables report the number of inflows recorded in the last 12 months prior to the observation.

where i refers to the province and, according to the frequency of the observations, t refers to the quarter. $a_{i,t}$ is the ratio between law reports for money laundering and law reports for source crimes registered in province i in the 12 months preceding time t, and represents our measure of criminal infiltration into the legal economy, i.e. provincial vulnerability.

$r_{j,t}$ is the discount rate on investment in both legal and illegal activities (since data on interest rates on bank deposits are on a regional basis j is an index of region), whereas $i_{Ai,t}$ is the return on legal investments, i.e. the ratio of real GDP to total bank loans in our case. $p_{Ci,t}$ is the percentage of source-crimes with known author, that is our measure of the likelihood of source-crime apprehension, while $p_{Ai,t}$ is related to the activities set up by different authorities in order to contrast money laundering. Parallel to source-crimes, we include in $P_{Ai,t}$ the percentage of crimes for money laundering with known author.

Among the tools set up to contrast money laundering we are particularly interested in the lagged value of suspicious transaction reports in relation to the economic dimension of the province, captured by its GDP ($p(susp)_{Ai,t-1}$). We also account for all the three variables representing the instruments through which money laundering takes place (bank deposits, cash accruing to the Central Bank, and real estate transactions, all divided by GDP) ($ML\ devices_{Ai,t-1}$). We also add the length of criminal trials as a general measure of deterrence against illegal conducts (both $p_{Ai,t}$ and $p_{Ci,t}$).

Next, according to the theoretical model we use the one-quarter lagged absolute value of source crime law reports in order to include a measure of the initial capital originating from illicit activities ($K_{i,t-1}$).[12] Finally, $\mu^a{}_i$ and $\delta^a{}_t$ are respectively province and time fixed-effects, while $e^a{}_t$ is an idiosyncratic error term.

To concentrate on the mechanism of reporting suspicious transactions we initially estimate equation (3.1) including only the ratio of transactions transmitted to the Bank of Italy ($p(susp)$) to provincial GDP, along with time and province fixed-effects (model (a)). In a second specification (model (b)) we add the instruments used to set up money laundering operations (*ML devices*). In model (c) we include a second equation (3.2) modelling the mechanism of reporting suspicious operations:

$$\begin{aligned} p(susp)_{i,t-1} &= \gamma_0 + \gamma_1 r_{j,t-1} + \gamma_2 i_{A,i,t-1} + \gamma_3 p_{A,i,t-1} + \gamma_4 ML\ devices_{i,t-1} \\ &\quad + \gamma_5 V(ML\ devices)_{i,t-1} + \gamma_6 p_{C\ i,t-1} + \gamma_7 K_{i,t-1} + \mu_i^s + \delta_t^s + e_{i,t}^s \end{aligned} \tag{3.2}$$

[12] Note that equation (3.1) is set up so as to reproduce the structure of the model of section 2 in every time period. In details, in every quarter (time 0 in the model) a criminal must decide how to allocate a given amount of illicit revenues realized in the previous period to either legal or illegal activities (i.e. the percentage to be washed against the percentage to be kept in the illegal sector). The choice depends upon the factors representing incentives to invest in one or the other sector in the current time period (0) and in the next period (1). Due to autocorrelation of most of these factors (i.e., the independent variables) we only consider their current time value (at time 0). We lag suspicious transaction reports and money laundering devices to account for the time required for the former to eventually evolve into law reports. Regressions performed using the variables one quarter ahead (at time 1) provide similar outcome.

where V(*ML devices*) is a measure of volatility (the standard deviation) of each ML device computed across the four quarters preceding the time in which signaling takes place. The inclusion of equation (3.2) is important for two main reasons.

First, the system of two jointly estimated equations (3.1)-(3.2) allows identifying to what extent money laundering operations are detected by the suspicious operation signaling mechanism. More precisely, the vector of parameters γ_4 indicates how efficiently each individual device is exploited by intermediaries and professionals to filter money laundering operations through the signaling mechanism. In the first equation of the system, instead, β_5 captures the share of money laundering operations *directly* accruing to the National Investigation Authorities[13] (as an outcome of apprehension mechanisms other than conveying information towards the FIU, such as investigations on other crimes which incidentally detect money laundering), which therefore elude the suspicious operation signaling mechanism.

Second, provided that the variables related to the suspicious operations transmission ($V(ML\ devices)_{i,t-1}$) are not correlated with unmeasurable characteristics of vulnerability (e^a_t), this enriched version of the model helps addressing the causal relationship between an increase in the frequency of signals for suspicious operations on vulnerability to money laundering.[14]

Finally, we further deepen the analysis including all regressors indicated in equation (3.1) (model (d and e)).

The model in all its five variants ((a)-(e)) is estimated through Three-Stage Least Squares (see Zellner 1962). Results are reported in Table 2 (equation for the vulnerability to money laundering), Table 3 (equation for suspicious transactions reports).

3.3 Results

Throughout this section we will mostly concentrate on interpreting the regression output in Table 2, which corresponds to the estimation of equation (3.1) regarding the impact of suspicious transactions reported to the FIU on vulnerability to money laundering (*a*) and the relationship between the latter and other variables related to crime apprehension. We mainly address our comments on model (e) since this specification is the most comprehensive and reliable version among those proposed in the empirical analysis. Estimates of the vulnerability to money laundering correspond to column (e1) in Table 2, while the estimated parameters of the other equations belonging to model (e) are reported in Table 3 (column (e2)).[15]

Focusing on column (e1) in Table 2, it is interesting to observe that the parameter associated to the ratio of suspicious transactions reports to GDP is negative. Considering that all variables are in logs, we can infer

[13] *Nucleo Speciale di Polizia Valutaria - Guardia di Finanza* (NSPV), Anti-Mafia Investigation Directorate (*Direzione Investigativa Antimafia*, DIA), and National Anti-Mafia Prosecutor (*Procura Nazionale Antimafia*, PNA).
[14] Statistical tests support the absence of correlation. See Wooldridge, 2010 for details on identification issues.
[15] Note that estimates are for the period 2009-2013 since we lose 4 quarters due to lags.

that an average increase of 10% in the number of suspicious transactions reported every billion euro of GDP (approximatively from 27 to 30) ends up decreasing vulnerability to money laundering by 1%.[16]

Going back to the discussion in the first part of this section we offer at least two possible explanations for this outcome. The first is that an increasing number of suspicious transaction reports conveyed towards the FIU reduces law reports for money laundering because it could be interpreted by criminals as a way of strengthening the reprehension activity on money laundering. Data on suspicious transactions are indeed publicly available on the web,[17] and therefore their increase could represent a threat for criminals, to the same extent as an increase in the crime detection rate may warn them (see below). The second explanation is that an increasing number of suspicious transactions could make the National Investigation Authorities less efficient in managing the information coming from the signaling bodies. This may slow down the process of screening, thus producing less law reports, *ceteris paribus*.

It is unquestionable that these two contrasting explanations deserve future research to be disentangled. However, we are in the position to exclude that this result is a spurious one, i.e. driven by the presence of *unmeasurable* factors in equation (3.1) that may contemporaneously affect the number of suspicious operations/GDP and our measure of vulnerability to money laundering. As in a previously mentioned example more suspicious operations transmitted are originated by an intensified activity on source-crimes, both a and the ratio of suspicious transaction reports to GDP could be affected. Both a proxy of the volume of source-crime activities among the regressors ($K_{i,\ t-1}$) and the presence of ($V(ML\ devices)_{i,t-1}$) in equation (3.2) allow excluding the possibility that any unmeasurable elements in (3.1) create bias.

All the other parameters in Table 2 have almost the expected sign, according to the theoretical model in section 2. First, the investment discount rate (Interest rate paid on deposits) is negatively associated to our measure of vulnerability, whereas the rate of return in the legal investment (Real GDP/Bank loans) does the opposite, although the evidence is weakly significant. Second, there is a significant negative relationship between the share of money laundering crimes with known author and vulnerability, plausibly indicating that the probability of detection is accounted for by criminals (this is in line with dalla Pellegrina, 2008a). A similar explanation holds also for the length of criminal trials though this effect appears less systematic as involving only one specification over five (column (d1), Table 2). Third, as predicted by the model, the initial quantity of funds to be invested either in the legal or in the illegal sector (proxied by source-crime law

[16] For simplicity define the dependent variable ML suspicious transactions/ GDP (lag) as the ratio between the number of ML suspicious transactions and GDP in billion euro. Referring to Table 1 this transformation implies that there are on average 27 suspicious transactions per province every billion euro. The estimated parameter associated to ML suspicious transactions/ GDP (lag) in column (e1) in Table 2 would end up being divided by 1,000 and become 0.014 We could interpret it as follows: For a 10% increase in the dependent variable, the expected increase in the independent variable when suspicious transaction reports/GDP increases by 10% is [1-1.01^(-0.014)]% = -1%.
http://www.ats.ucla.edu/stat/mult_pkg/faq/general/log_transformed_regression.htm

[17] https://uif.bancaditalia.it/pubblicazioni/quaderni/2009/boll-sem-2009-1/Bollettino_semestrale_I_sem_2009.pdf

reports), exhibits negative sign. Fourth, the negative sign associated to the share of source- crimes with known author and vulnerability does not seem to match the predictions of the theoretical model. The emerging negative relation between the share of source- crimes with known author and vulnerability might be interpreted as the fact that efficient detection against source-crimes discourages even money laundering because both criminals perceive the institutional response to crime as strong and effective in general, and funds to be laundered are riskier to be generated, in particular.

There is also some noteworthy evidence from the sign associated to the vector *ML devices*. Combining the output of Tables 2 and 3 we can infer that financial intermediaries are far more likely to report suspicious operations when the latter involve abnormal amounts of cash transactions, particularly when there is an increase of the volume of inflowing currency, which is eventually transferred to the Central Bank (the parameter associated to Cash accruing to Central Bank/ GDP in Table 3 is always positive and strongly significant). However, it seems that intermediaries are less likely to account for anomalous changes in the volume of deposits when transmitting information to the FIU (the parameter associated to Bank deposits/ GDP in Table 3 is never significant). However, looking at Table 2 (columns (b1)-(e1)), the positive sign associated to Bank deposits/GDP suggests that money laundering operations conducted using the deposit device, although significantly evolving into law reports (perhaps stemming from investigations on other crimes), elude the FIU signaling mechanism. Real estate transactions, instead, do not provide any significant evidence in terms of evolution into law reports for money laundering, neither direct, nor intermediated by notaries.[18]

As for the variables exploited to address the aforementioned causality problems ((*V*(*ML devices*)) , a strongly significant positive relationship is observed between the volatility of all bank tools (cash, deposits, real estate transactions) and the number of suspicious transactions. If, according to the discussion above, we correctly interpret volatility as a confounding factor for the signaling bodies, estimated parameters indicate that when signals become less clear, *ceteris paribus,* intermediaries and notaries tend to report more suspicious transactions to the FIU.

[18] One possible explanation is that we are endowed with the number of transactions, whereas the amount of the transactions could provide more clear-cut insights.

Table 2: Vulnerability to Money Laundering – Italian provinces 2009-2013

Dependent variable: ML law reports/Source crime law reports_1	**(a1)**	**(b1)**	**(c1)**	**(d1)**	**(e1)**
Interest rate paid on deposits				-0.163**	-0.143**
				(0.078)	(0.069)
GDP/Bank loans				0.211	0.036*
				(0.337)	(0.019)
ML suspicious transactions/ GDP (lag)	-1.287***	-4.471***	-25.258***	-18.035***	-13.796***
	(0.006)	(0.908)	(7.034)	(4.200)	(3.292)
Cash to Central Bank/ GDP (lag)		0.752	1.219	0.827	0.771
		(0.481)	(3.380)	(2.094)	(1.658)
Bank deposits/ GDP (lag)		0.970***	0.991**	0.741**	0.814***
		(0.266)	(0.427)	(0.346)	(0.283)
Real estate transactions/ GDP (lag)		0.028	0.161	0.161	0.153
		(0.184)	(0.298)	(0.250)	(0.204)
ML crimes with known author				-0.091***	-0.107***
				(0.034)	(0.027)
Source crimes with known author				-1.407***	-1.320***
				(0.246)	(0.208)
Length of criminal trials				0.095*	0.067
				(0.055)	(0.067)
Source crime law reports (lag)				-0.490***	-0.437***
				(0.066)	(0.054)
Constant	0.499***	0.516**	0.427	9.084***	8.528***
	(0.050)	(0.201)	(0.420)	(1.146)	(0.958)
Year fixed-effects	yes	yes	yes	yes	yes
Province fixed-effects	yes	yes	yes	yes	yes
R2	0.5982	0.6092	0.2777	0.3521	0.4805

Columns: (c1) jointly estimated with equation (c2) in Table 3; (d1) jointly estimated with equation (d2) in Table 3; (e1) jointly estimated with equation (e2) in Table 3 and equation (e3) in Table 4.
All variables are in (natural) logs. * p<0.1; ** p<0.05; *** p<0.01. Obs. 1,648.
Frequency of data: quarterly. Each observation refers to the variable measured on an annual basis.

Table 3: Suspicious transactions transmitted to the FIU – Italian provinces 2009-2013

Dependent variable: **ML suspicious transactions/ GDP (lag)**	**(c2)**	**(d2)**	**(e2)**
Interest rate paid on deposits (lag)		0.001	0.001
		(0.003)	(0.003)
GDP/Bank loans (lag)		-0.051***	-0.052***
		(0.010)	(0.010)
ML suspicious transactions/ GDP (lag)			
Cash accruing to Central Bank/ GDP (lag)	0.374***	0.275***	0.267***
	(0.048)	(0.055)	(0.057)
Bank deposits/ GDP (lag)	-0.009	-0.014	-0.012
	(0.014)	(0.014)	(0.014)
Real estate transactions/ GDP (lag)	0.015	0.004	0.002
	(0.010)	(0.010)	(0.001)
ML crimes with known author (lag)		0.004***	0.004***
		(0.001)	(0.001)
Source crimes with known author (lag)		-0.022***	-0.024***
		(0.008)	(0.008)
Length of criminal trials (lag)		0.007**	0.007**
		(0.003)	(0.003)
Source crime law reports (lag)		-0.006***	-0.005**
		(0.002)	(0.002)
Std. Dev. Cash accruing to Central Bank/ GDP (lag)	0.535***	0.584***	0.552**
	(0.171)	(0.197)	(0.242)
Std. Dev. Bank deposits/ GDP (lag)	0.240***	0.272***	0.301***
	(0.074)	(0.076)	(0.085)
Std. Dev. Real estate transactions/ GDP (lag)	0.056***	0.072***	0.072***
	(0.015)	(0.013)	(0.014)
Constant	-0.040***	0.108***	0.112***
	(0.011)	(0.039)	(0.040)
Year fixed-effects	yes	yes	yes
Province fixed-effects	yes	yes	yes
R2	0.7802	0.7878	0.7878

Columns: (c2) jointly estimated with equation (c1) in Table 2; (d2) jointly estimated with equation (d1) in Table 2; (e2) jointly estimated with equation (e1) in Table 2 and equation (e3) in Table 4.
All variables are in (natural) logs. * p<0.1; ** p<0.05; *** p<0.01. Obs. 1,648.
Frequency of data: quarterly. Each observation refers to the variable measured on an annual basis.

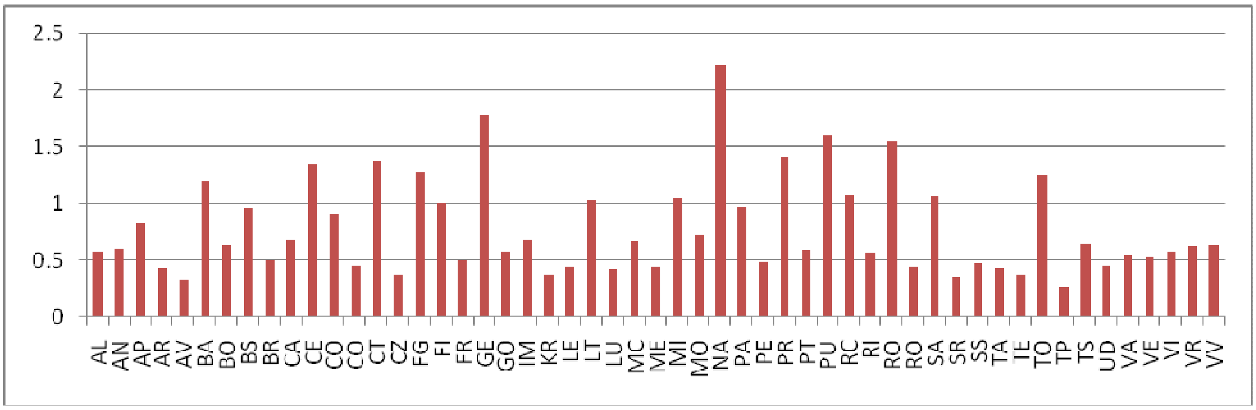
Local specificities of vulnerability and areas that are idiosyncratically vulnerable

From the broad concept of institutional vulnerability, we can extrapolate the contribution of characteristics that *systematically* affect each province with different intensity. Some provinces, in fact, are steadily vulnerable to money laundering, regardless changes in both detection and prosecution devices, in their economic performance, and in all other elements that have been individually specified in equation (3.1).

As aforementioned, some examples of unmeasurable heterogeneities across provinces could be related to the characteristics of the local administrations, cultural factors, population specialization in specific criminal activities, and all phenomena that can be considered deeply rooted in the society. It is not by chance that in the graph reported in Figure 2 some notorious provinces stand out more than others. One is Naples (NA), which has worldwide recognized propensity towards crime tolerance. The second is Prato (PR), a province in Tuscany where a Chinese community has long established its business activities in the textile sector, which is particularly vulnerable to counterfeiting and subsequent money laundering activities.[19]

The policy implication stemming from this stage of the analysis is to set up the conditions to promote cultural changes in the areas of the country which are *systematically* vulnerable to money laundering. Such activities will not typically involve police intervention, or crime repression to a large extent, but should be rather intended to act on crime *prevention* and social capital increase, so as to enhance crime awareness and social stigma against illegal attitudes.

Figure 2. Unmeasurable heterogeneity across provinces Italian provinces 2009-2013

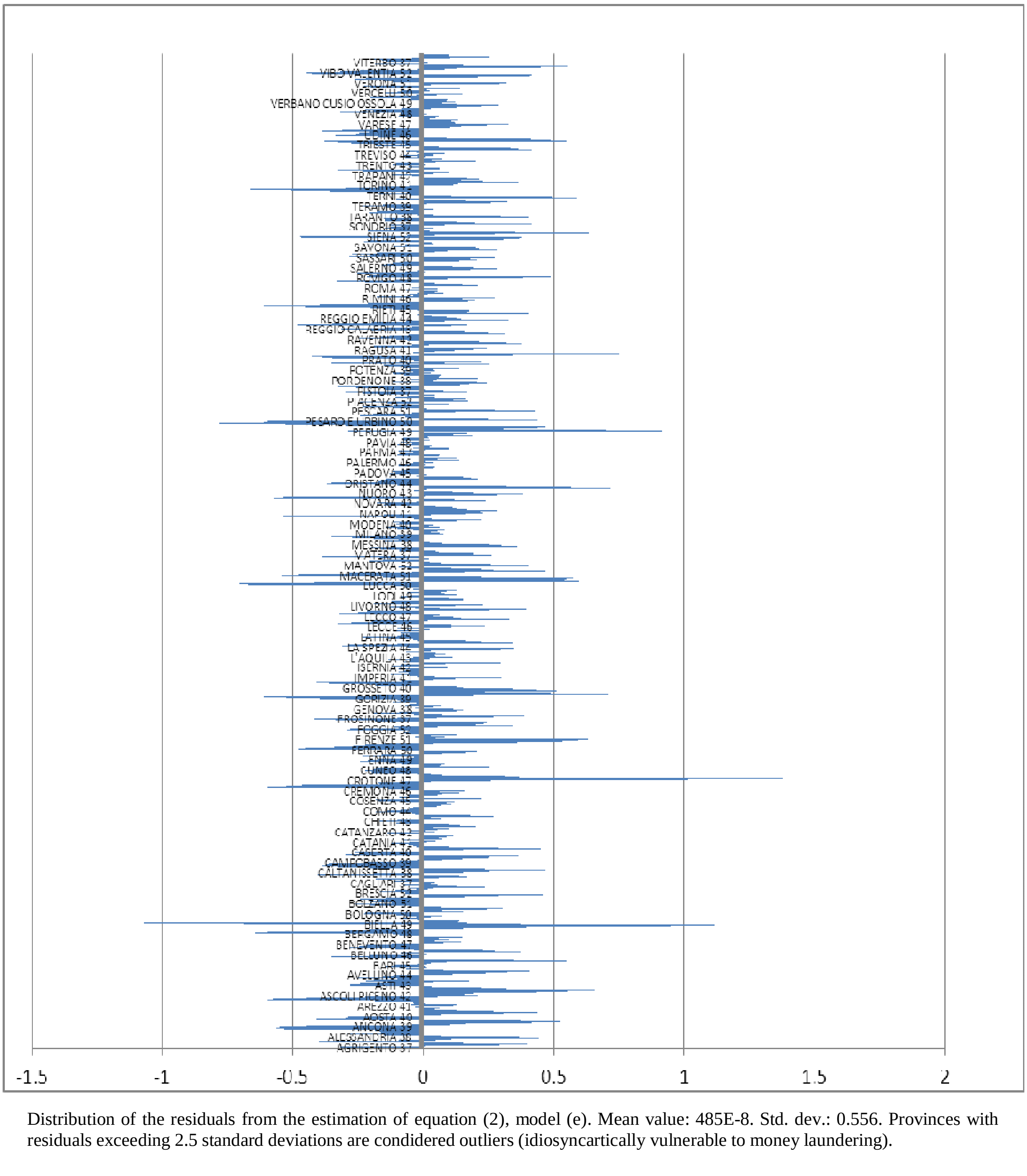


As anticipated at the beginning of this empirical section we seek to identify the areas that have been *occasionally* subject to “abnormally” intense money laundering activity. Therefore, we concentrate on the estimated residual component of equation (3.1). Looking at random peaks in the residuals’ distribution (see

[19] A recent investigation for money laundering has taken palace in province of Prato. It has involved 279 people, including the Bank of China for not reporting suspicious transactions.

Figure 3) we can detect in which provinces and periods vulnerability to money laundering has been particularly intense.

Figure 3. Random peaks in the residuals' distribution: idiosyncratic vulnerability



Distribution of the residuals from the estimation of equation (2), model (e). Mean value: 485E-8. Std. dev.: 0.556. Provinces with residuals exceeding 2.5 standard deviations are condidered outliers (idiosyncartically vulnerable to money laundering).

Statistical diagnostics suggest that residuals are normally distributed with mean value equal to 485E-8, that is approximately zero. Hence, to identify the most relevant outliers in the distribution we use the Chauvenet's criterion, finding a probability band, centered on the mean of the residuals' distribution, that should reasonably contain all plausible values of the residuals. Values that lie outside this probability band can be considered as outliers. We set the band height at 2.5 standard deviations from the mean of the residual distribution.

There are some recognizable events that can be ascribed to occasional vulnerability to money laundering. The province of Crotone, for instance, is known for the presence of firms involved in the business of recovery and disposal of toxic waste.[20] According to our data Crotone exhibits a constant increase in the use of cash throughout all the period of analysis. Bank deposits also show a growing pattern from 2001 (from which we have information) until the peak of 2009. Biella, the second most idiosyncratically vulnerable province, shows anomalous peaks in the use of cash, especially in 2008. It is worth noticing, however, that Biella and Crotone resulted vulnerable to money laundering in 2012 and 2013. This suggests that deposits and cash movements − the second often identified through the system of reporting suspicious transactions as highlighted by our empirical analysis −can be a valuable predictors of successful anti-money laundering operations. According to our analysis, other idiosyncratically vulnerable provinces are Prato, Gorizia, Pesaro-Urbino, Ascoli Piceno, Siracusa, Florence, Terni, Macerata, and Oristano.

4. Conclusions

The aim of this paper was to identify indicators of local vulnerability to money laundering which are at the same time scientifically robust and empirically feasible.

From a methodological perspective, we have considered criminals as rational investors who account for both risks and returns of investing illicit revenues in either legal or illegal markets. Money laundering transforms the proceeds of crime into legitimate assets, thereby increasing the degree of penetration of criminal organizations into the legal sector, and enhancing the diversification of criminals' income and wealth. When deciding the dimension of their money laundering activity criminals evaluate specific features characterizing legal and illegal projects of investment, both in terms of return and risk. They also account for the probability of detection and incrimination of different types of illegal activities, that is both source-crimes and money laundering. The optimal decision regarding the extent to which money is laundered rather than (re-) invested in the illegal sector defines geographical vulnerability as a function of the parameters of our model.

The model has been used in the empirical analysis to investigate the impact of institutional and economic factors on the vulnerability of the legal sector to criminal infiltration in the Italian provinces. We obtained three results.

First, testing the predictions of the theoretical model, we have highlighted the effects of crime prevention policies on the vulnerability of Italian provinces to money laundering *(institutional vulnerability)*. Reporting

[20] A large investigation against money laundering has been conducted in 2013 by the Financial Police.

suspicious transactions to the Financial Intelligence Unit (FIU) deserves attention. We found that an average increase of 10% in the number of suspicious transactions reported every billion euro of GDP ends up decreasing vulnerability to money laundering by 1%. We interpreted this result as a positive signal of the deterring effect of an increasing number of suspicious transaction reports in shaping criminal investment decisions.

Second, the analysis has identified *unobserved heterogeneity across provinces*, that is local characteristics which are not individually measurable, which embed specific incentives or restraints to embark on money laundering activities. Such phenomena are mostly related to time-persistent institutional factors which are proper of a given province. Some features seem to be particularly relevant: other things being equal, the econometric results show that the most vulnerable provinces are likely to be those where ports and casinos are located.

Finally, we have pinpointed the areas that have been occasionally subject to “abnormally” intense money laundering activity (*idiosyncratic vulnerability*).

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Figure A1.1

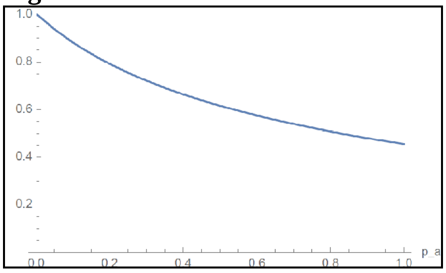


Figure A1.2

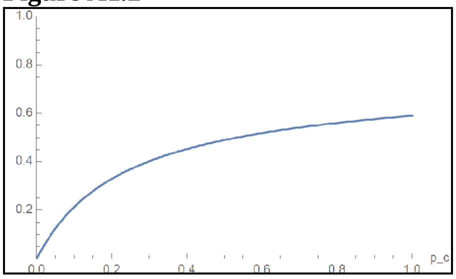


Figure A1.3

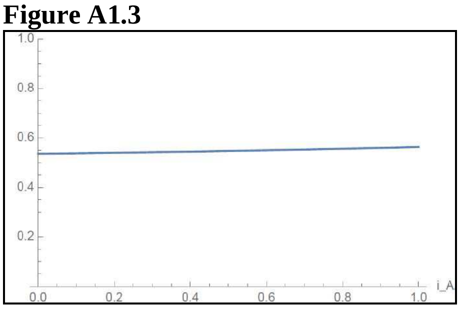


Figure A1.4

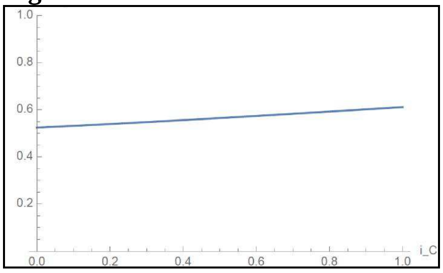


Figure A1.5

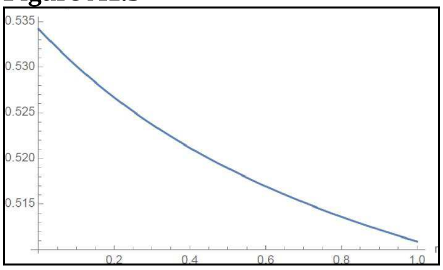
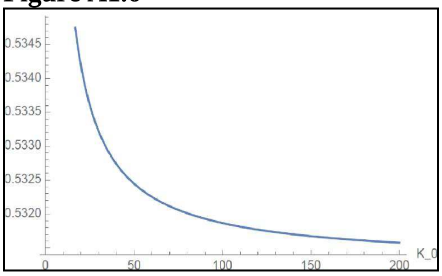


Figure A1.6



Appendix 2

Figure A.1 – Suspicious transaction reports, 2008-2012

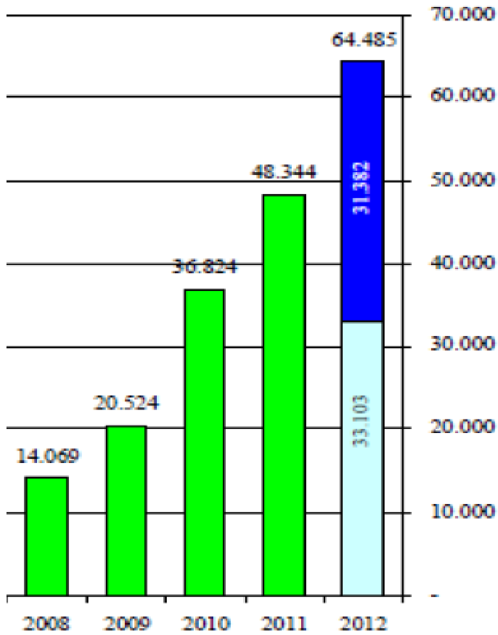
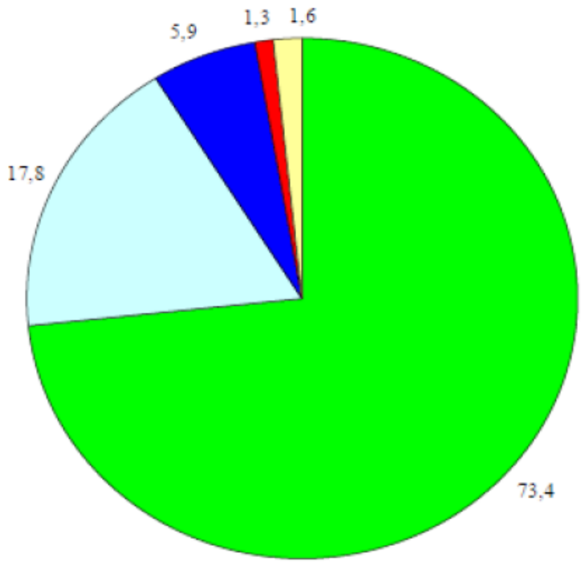


Figure A.2 – Signalling bodies, 2008-2012



Green: banks; light blue: postal offices; blue: other financial intermediaries; red: electronic money institutes; yellow: other.

Figure A.3 – Law reports for money laundering every 100,000 inhabitants, 2008-2012

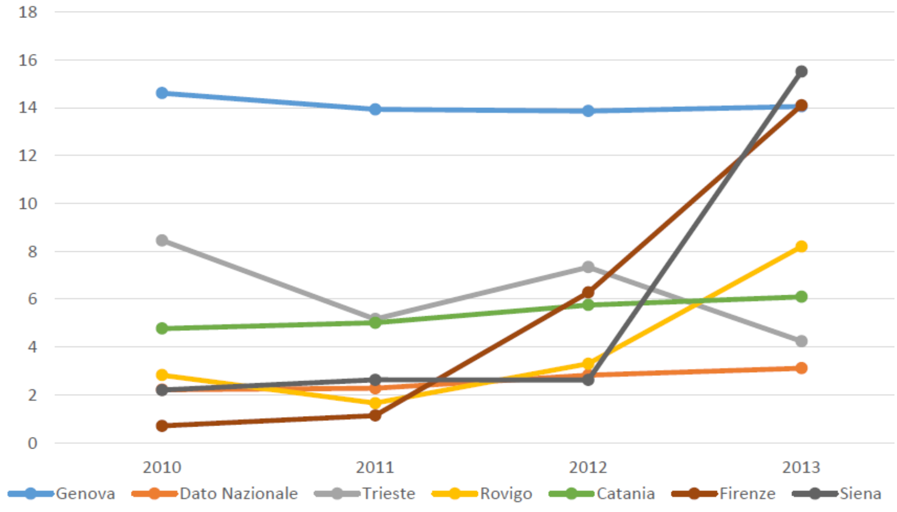


Figure A.4 – Law reports with known author (%), 2008-2013