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Are Bankers "Crying Wolf"? The Risk-based Approach to Money-Laundering Regulation and Its Effects

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Abstract

Excessive and useless reporting, called the "crying wolf effect", is a crucial shortcoming that any anti-money laundering (AML) design aims to address. For this reason, in recent years, AML policies in both the US and Europe have switched from a rule-based approach to a risk-based approach. This study theoretically and empirically investigates whether the risk-based approach delivers the expected results. The theoretical model shows that a trade-off can emerge between accuracy – fewer type-I and type-II errors – and deterrence. The empirical analysis, conducted after the risk-based approach was introduced in Italy, confirms such a trade-off. More specifically, deterrence is maximized, while accuracy is sacrificed. In this respect, the data suggest that Italian bankers are likely to "cry wolf".

Keywords: Anti-money laundering; suspicious transaction reporting; standard of evidence; type-I error; type-II error; deterrence; Italy.

JEL Classification: G2, K2, K4.

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1. Introduction

Excessive and useless reporting, known as the “crying wolf effect” (Takats, 2011), is a crucial shortcoming that any anti-money laundering (AML) design aims to address and fix. The “crying wolf effect” harms the informational value of reports that banks and other professionals are obliged to file in order to comply with AML regulations.

The AML system now in place in many regions, including much of Europe and the United States, consists of a three-layer hierarchy of enforcers: financial intermediaries and other professionals; a financial intelligence unit (FIU), which is normally established at the central bank; and the judiciary system. On the first level, financial intermediaries and other professionals are required to monitor all financial transactions and report suspected acts of money laundering to the FIU by filing a suspicious transaction report (STR).

In the past, the AML system followed a rule-based approach. Financial intermediaries and other professionals used a set of certain criteria (determined by the law and the FIU) to identify suspicious transactions and report them to the FIU. In that system, the role of financial intermediaries and other professionals was relatively passive. One of the main problems of the rule-based approach was the high number of STRs erroneously issued by financial intermediaries and professionals. The high incidence of type-I errors (false positives) in the rule-based AML system was considered inefficient because it wasted the FIU’s resources. Moreover, it was ineffective in deterring money laundering, and detrimental for intermediaries and professionals (especially from a reputational perspective). On the other hand, simply raising the bar by imposing stricter rules and criteria for reporting a transaction as suspicious to the FIU was not a solution. In this regard, false negatives represent an additional problem for AML systems, as decisions to not report potential money-laundering transactions (type-II errors) both dilute deterrence and make the financial system less reliable (Demetis, 2010).

Between 2007 and 2010, AML policies in both the US and in Europe switched from a rule-based reporting system to a risk-based system in which all layers of the system need to respond to money-laundering threats in ways that are proportionate to the risks involved.[1] In particular, financial intermediaries and other professionals are required to play an active role in identifying suspicious transactions (Black & Baldwin, 2010; Dalla Pellegrina & Masciandaro, 2009). They must exploit their knowledge and other information regarding the financial habits of their customers (the know-your-customer (KYC) approach) to better determine which transactions should be reported as suspicious to the FIU. They must also apply their subjective judgment to assess the actual risk that a transaction is money laundering. In fact, intermediaries and

[1] https://www.anti-moneylaundering.org/EU_Chart.aspx

professionals are required to adjust their reporting criteria and, therefore, move up or down their decisional bars (i.e., a type of standard of evidence) when deciding whether to report a transaction to the FIU depending on the actual risk of money laundering (Axelrod, 2017; Lowe, 2017).

The risk-based approach was introduced mainly to avoid over-reporting to the FIU without allowing type-II errors to explode. In general, the aim of the risk-based AML system is to increase the reliability and accuracy of the STRs that financial intermediaries and other professionals (the first level of the AML system) send to the FIU (the second level of the AML system). In this vein, the KYC approach (see Jeans, 2016) should allow financial intermediaries and other professionals to reduce the number of both type-I and type-II errors on the first level of the AML system. At the second level of the AML system, the FIU analyses the collected STRs and reports those transactions that it deems to be money-laundering acts to the judicial authority. Type-I errors made by financial intermediaries and professionals, and submitted in STRs, are typically dismissed by the FIU because they are not considered true money-laundering transactions.[2] The judicial authority, the third level of the AML system, collects the reports from the FIU and decides whether to issue a referral to trial.

Type-II errors committed on both the first and second levels of the AML system can be detected by the judicial authority. The latter also collects reports on money laundering that come from institutions other than the FIU and from actors other than financial intermediaries and professionals. For instance, money laundering can be detected by the police while investigating other crimes. Sometimes criminal organizations' confessions describe how illegal funds are laundered and how those activities avoid the AML measures.[3] Although possible, errors at the level of the law-enforcement system are not included in this analysis, which focuses on the first level of the AML system.

As discussed by Unger and van Waarden (2009), despite the aim of making the (first level) of the AML system more reliable, the impact of the risk-based approach has differed across countries. In some countries, over-reporting has decreased and the overall quality of the reported information has improved. However, this is not the case in other countries.[4]

[2] The FIU can also commit both type-I and type-II errors (i.e., filing a report when the transaction is not a money-laundering act and not filing a law report when the transaction is a money-laundering act, respectively). However, we are focused on the efficiency of the first level of the AML system level. As such, we assume that the second-level authorities have perfect foresight.

[3] See Arnone and Borlini (2010), and Barone and Masciandaro (2019).

[4] In particular, Unger and van Waarden (2009) show that over-reporting decreased and quality increased in the Netherlands. In other countries, including the US, over-reporting increased with detrimental effects on quality (the "crying wolf effect"). However, according to Gara et al. (2019), reporting activity in Italy increased without reducing the quality of the information. In fact, the quality of that information improved.

This study aims to investigate whether the risk-based approach introduced in Italy in 2009 had the expected results in terms of increased reporting accuracy and, in particular, a lower rate of type-I errors at the first level of the AML system. The analysis is based on a theoretical model that describes the relations between the standard of evidence, type-I errors, type-II errors, and their sum (a measure of accuracy), and the deterrence of money-laundering activities. In general, the empirical aim is to test the most important implications of the theoretical model using data from the Italian FIU starting from the point at which the risk-based approach was introduced. We use factorial analysis supported by an approach based on the concept of "sufficient statistics" (Chetty, 2009). Our results show an increase in type-I errors following the introduction of the risk-based system. Based on this result, we make inferences regarding the trend in type-II errors using the predictions of the theoretical model. We conclude that type-II errors decreased in the period of interest.

The paper is organized as follows. In the next section, we present the theoretical framework. The theoretical results are mainly presented using a graphical approach. We empirically assess the model in section 3. In section 4, we present our conclusions and discuss several policy implications.

2. The model

Financial intermediaries and professionals, the FIU and the judicial authority make their decisions basing on pieces of evidence that support or contradict the hypothesis that a certain transaction involves money laundering. In particular, financial intermediaries and professionals decide whether to issue an STR for a given transaction mainly by taking the transaction's attributes and the customer's characteristics into account (Gara & Pauselli, 2015).

In the risk-based approach, financial intermediaries and other professionals should also apply the KYC principles in order to better select the transactions that should be reported to the FIU as suspicious. The subjective judgments of these actors are relevant and must be considered together with all of the other elements when assessing the risk that a transaction is an act of money laundering. Financial intermediaries and professionals issue an STR when the evidence supporting the idea that a transaction involves money laundering is greater than a certain threshold, which is used as a type of *standard of evidence*.

2.1 Evidence and standard of evidence

We model the decision to issue an STR by developing the intuition found in Rizzolli and Saraceno (2013). More specifically, we assume that the net evidence considered by the agent is the sum of indications of guilt, quantified and assigned a positive sign, and the sum of indications of innocence, quantified and assigned a negative sign. In particular, we assume that each attribute of a transaction, including subjective judgements on the parties involved in the transaction, is a piece of evidence that takes a positive sign when it is consistent with the suspicion of a money-laundering act and a negative sign when it does not support that suspicion. Financial intermediaries and professionals observe the net evidence, e. They then issue an STR when the net evidence is greater than a certain threshold $\hat{e}$, which is their standard of evidence.

We do not consider how the net evidence is produced. We model the net evidence in favour of a suspect of money-laundering activity as an exogenous continuous random variable, E. On the one hand, we consider the distribution of the net evidence, E, conditional on the transaction being an act of money laundering and the client being guilty of money laundering. On the other hand, we consider the distribution of the net evidence, E, conditional on the transaction not being an act of money laundering and the client being innocent.

We assume that both conditional distributions are normal – that is, $(E|Guilty) \sim N(\mu_G, \sigma_G^2)$ and $(E|Innocent) \sim N(\mu_I, \sigma_I^2)$. $g_E(e)$ is the probability density function of E conditional on the client being guilty, and $G_E(e)$ is its cumulative distribution function. Analogously, $i_E(e)$ is the probability density function of E conditional on the client being innocent, and $I_E(e)$ its cumulative distribution function. We also assume $\mu_I < 0 < \mu_G$, $\mu_I = -\mu_G$ and $\sigma_I^2 = \sigma_G^2$. Therefore, $i_E(e)$ and $g_E(e)$ are symmetrical with respect to the vertical axis (i.e., $i_E(-e) = g_E(e)$), with $i_E(0) = g_E(0)$. We assume normality for the sake of simplicity (many of the model's implications are illustrated graphically by assuming normal conditional probability distributions of the net evidence). However, this assumption can be relaxed by simply assuming symmetrical distributions crossing once in 0 (see Dalla Pellegrina, Di Maio, & Saraceno, 2020).

These assumptions imply that positive net evidence suggests a greater probability of the transaction being an act of money laundering, while negative net evidence suggests a greater probability of the transaction not involving money laundering. Moreover, the assumptions are consistent with the idea that, on average, the net evidence is positive for a money-laundering transaction and negative for a transaction that does not involve money laundering.[5] This idea is the pillar of the AML system, which is based on the assumption that financial intermediaries and professionals can assess the risk that a transaction is an act of money laundering by considering the transaction's attributes and their knowledge of their clients.

In summary, the conditional probability distribution functions of the net evidence are as follows:

[5] Indeed, it is $G_E(e) \leq I_E(e)$. In other words, $G_E(e)$ has first-order stochastic dominance over $I_E(e)$.

$$\begin{cases} i_E(e) > g_E(e), for\ e < 0 \\ i_E(e) = g_E(e), for\ e = 0 \\ i_E(e) < g_E(e), for\ e > 0 \end{cases} \tag{1}$$

As $e > 0$ increases, it becomes less likely that positive net evidence, e, will be collected for an innocent client. In reverse, as $e < 0$ decreases, it becomes less likely that negative net evidence, e, will be collected for a guilty client.

Figure 1 provides an example of two probability density functions, $i_E(e)$ and $g_E(e)$. It was created by applying $\mu_G = \mu_I = 7$ and $\sigma_I^2 = \sigma_G^2 = 5$. Figure 2 shows the corresponding cumulative distribution functions, $I_E(e)$ and $G_E(e)$. The additional pictures illustrating the model are based on conditional probability distributions of the net evidence that are characterized by these parameters. Different parameters do not jeopardize the main implications of the model.

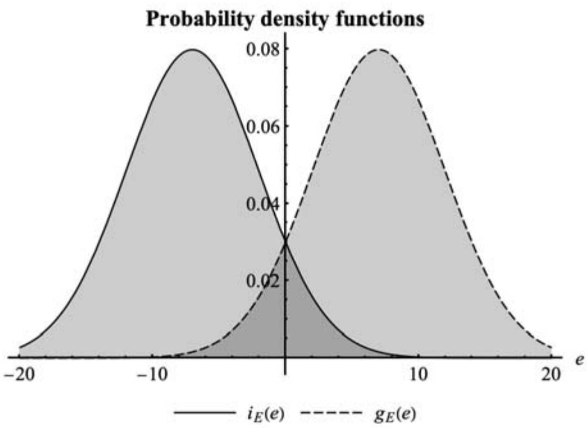


Figure 1 – Conditional probability density functions of e

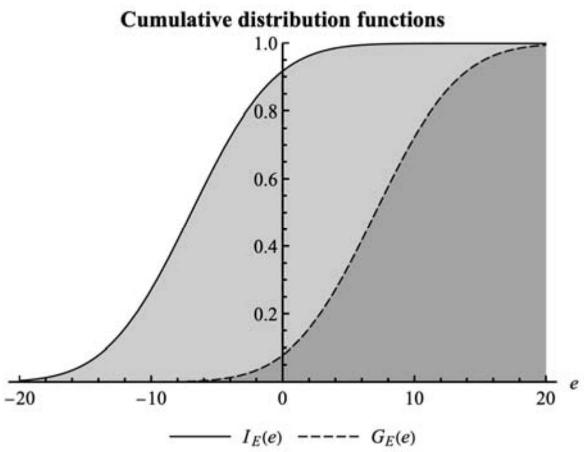


Figure 2 – Conditional cumulative distribution functions of E

2.2 The decision to issue or not issue an STR

Financial intermediaries and professionals issue an STR for a given transaction when they observe net evidence, e, that is greater than their standard of evidence, $\hat{e}$. Therefore, the probability of a correct STR being issued is $Pr[E > \hat{e}|Guilty] = 1 - G_E(\hat{e})$. Conversely, an STR is incorrectly issued for a transaction that is not an act of money laundering (type-I error) with a probability of $Pr[E > \hat{e}|Innocent] = 1 - I_E(\hat{e})$. Moreover, an STR is correctly not issued for a transaction that is not an act of money laundering with a probability of $I_E(\hat{e})$. Finally, an STR is incorrectly not issued for a money-laundering transaction (type-II error) with a probability of $G_E(\hat{e})$.

Figure 3 illustrates the probabilities of correctly or incorrectly deciding to report or not report a given transaction as functions of the standard of evidence, $\hat{e}$.

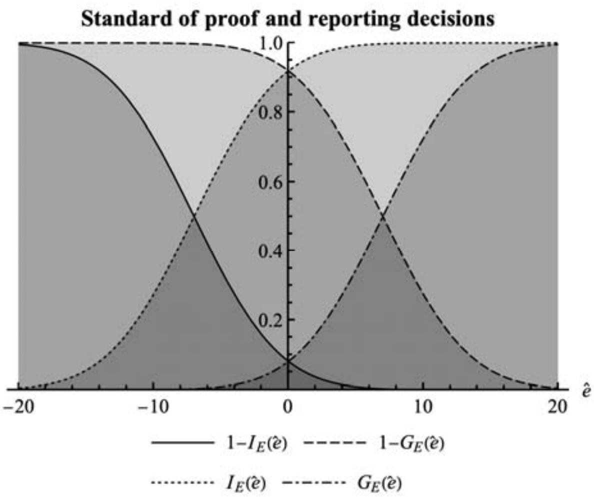


Figure 3 – Standard of evidence and probabilities of a correct or incorrect reporting decision

Note that the standard of evidence, $\hat{e} = 0$, can be seen as a *preponderance of evidence standard* (Demougin & Fluet, 2006; Lando, 2002). When a preponderance of evidence standard is applied, an STR is issued whenever the evidence is positive (i.e., it is more likely than not that the transaction is an act of money laundering). Indeed, for $\hat{e} = 0$, the probability of rightfully not issuing an STR conditional on the transaction not being an act of money laundering is equal to the probability of correctly issuing an STR conditional on the transaction being an act of money laundering.

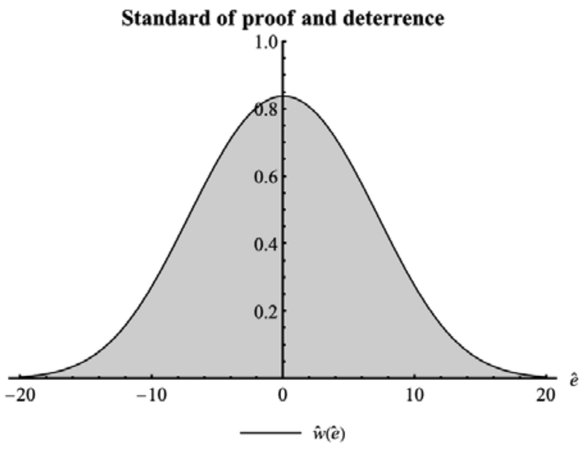
Finally, note that the probabilities of committing type-I and type-II errors for a given transaction depend on the overlap between $i_E(e)$ and $g_E(e)$ (see Figure 1). The greater the overlap, the higher are the probabilities of committing type-I and type-II errors when a preponderance of evidence standard is applied.

2.3 Standard of evidence and deterrence

We define $w > 0$ as the net benefit resulting from money laundering[6] and $S > 0$ as the expected sanction applied to the money launderer when an STR is issued.[7] A rational, risk-neutral individual undertakes a money-laundering transaction only when the expected utility, $w - S[1 - G_E(\hat{e})]$, is greater than the expected utility from abstaining, $-S[1 - I_E(\hat{e})]$. As above, $\hat{e}$ is the standard of evidence applied by financial intermediaries and professionals. Thus, a money-laundering transaction is committed when:

$$\begin{gathered} w - S[1 - G_E(\hat{e})] > -S[1 - I_E(\hat{e})] \\ w > S[I_E(\hat{e}) - G_E(\hat{e})] \equiv \hat{w}(S, \hat{e}) \end{gathered} . \tag{2}$$

We define $\hat{w}$ as the *deterrence threshold*. It is a function of the sanctions, S, and the standard of evidence that is applied by the signalling bodies when deciding whether to report the transaction to the FIU. The greater the deterrence threshold, $\hat{w}$, the greater the deterrence against money laundering. Figure 4 shows that, given the sanction S,[8] deterrence is at the maximum when a preponderance standard of evidence is applied (i.e., when $\hat{e} = 0$).



[6] The net benefit considered here is the gain that a money-laundering transaction would produce in the absence of law enforcement net of the gain that could otherwise be obtained legally (i.e., by obeying the law).
[7] In the real world, sanctions for money laundering are applied by the third level of the AML system, which is the judicial system. The expected sanction, S, that we consider is an estimation of the sanction applied by the judicial system conditional on the issuance of an STR.
[8] In Figure 4, sanction S is set equal to 1.

Figure 4 – Standard of evidence and deterrence

An inspection of Figure 4 leads to the first result of our model: given any sanction, *S,* the maximum deterrence threshold is achieved by setting the standard of evidence equal to 0 (the preponderance of evidence standard). This general result can also be analytically derived by simply recalling that $i_E(0) = g_E(0)$.[9]

RESULT 1: The standard of evidence that maximizes deterrence is $\hat{e} = 0$ (i.e., the preponderance of evidence standard).

2.4 A measure of money-laundering activity

By normalizing the population to 1, the probability that an individual decides to engage in a money-laundering transaction is:

$$Pr\ [w > \widehat{w}(S, \hat{e})]. \tag{3}$$

Obviously, in order to compute the probability of a money-laundering transaction, we need to know the probability distribution of *w*. As we do not know this distribution, we restrict ourselves to building a probability measure[10] consistent with the probability defined in (3).

Starting from the deterrence threshold expressed in (2), we define a probability measure of the subset such that the condition determining the probability expressed in (3) is verified for a given values of *w*. More specifically, we define the *money-laundering rate*[11] (*MLR*) as:

$$MLR(S, \hat{e}) = 1 - \widehat{w}(\hat{e}) = 1 - S[I_E(\hat{e}) - G_E(\hat{e})]. \tag{4}$$

This measure of money-laundering activity does not provide any additional insights with respect to what we observed in our definition of the deterrence threshold in the previous section.

[9] First-order condition of the maximization problem: $S[i_E(\hat{e}) - g_E(\hat{e})] = 0 \Rightarrow i_E(\hat{e}) = g_E(\hat{e})$ that is verified for $\hat{e} = 0$. The second-order condition is easily verified by recalling that the two conditional probability distribution functions of the net evidence are symmetric and cross (once) in $\hat{e} = 0$, so that $\frac{\partial i_E}{\partial \hat{e}}|_{\hat{e}=0} < 0$ and $\frac{\partial i_E}{\partial \hat{e}}|_{\hat{e}=0} = \frac{\partial g_E}{\partial \hat{e}}|_{\hat{e}=0}$.

[10] A *probability measure* on a set is a systematic way to assign a number to each suitable subset of that set, which is intuitively interpreted as its size. It takes the value of 1 on the whole space (and, therefore, takes all of its values in the unit interval [0, 1]).

[11] In order to guarantee that the *MLR* is between 0 and 1, we set $0 < S < 1/[I_E(0) - G_E(0)]$.

However, in the following, we analyse how reporting activity and its accuracy change according to the standard of evidence that is applied by the signalling bodies.

As expected (see Figure 5), for any given sanction S, the money-laundering rate, $MLR(\hat{e})$, is minimal when a preponderance of evidence standard is applied. Figure 5 is based on the usual assumptions about the conditional probability distributions of the net evidence (see Figure 1): S is set equal to 1 and the resulting minimum money-laundering rate $MLR(0)$ is approximately 15 percent.

LEMMA 1: The standard of evidence that minimizes the money-laundering rate is $\hat{e} = 0$ (i.e., the preponderance of evidence standard).

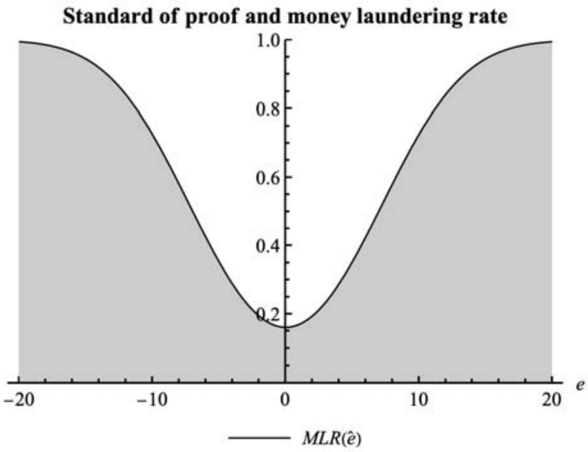


Figure 5 – Standard of evidence and money-laundering rate

2.5 Reporting activity, type-I and type-II errors, and overall accuracy

Given the applied standard of evidence and the related money-laundering rate, financial intermediaries and professionals observing all of the transactions that take place (100 percent) report a share of suspicious transactions to the FIU corresponding to:

$$STR(\hat{e}) = \underbrace{MLR(\hat{e}) \times \left(1 - G_E(\hat{e})\right)}_{Share\ of\ correct\ STRs} + \underbrace{\left(1 - MLR(\hat{e})\right) \times \left(1 - I_E(\hat{e})\right)}_{\substack{Share\ of\ erroneous\ STRs \\ (Type-I\ error\ incidence)}} \tag{5}$$

Figure 6 shows the share of transactions that are reported as suspicious ($STR(\hat{e})$) and its two components (i.e., correct and erroneous STRs (type-I errors)) as functions of the standard of evidence, $\hat{e}$.[12] We define the error rate, $ER(\hat{e})$, as the share of total transactions that imply an error – either type-I or type-II – by the signalling bodies. It corresponds to the total incidence of type-I errors and type-II errors:

$$ER(\hat{e}) = \underbrace{\left(1 - MLR(\hat{e})\right) \times \left(1 - I_E(\hat{e})\right)}_{Type-I\ error\ incidence} + \underbrace{MLR(\hat{e}) \times G_E(\hat{e})}_{Type-II\ error\ incidence} \tag{6}$$

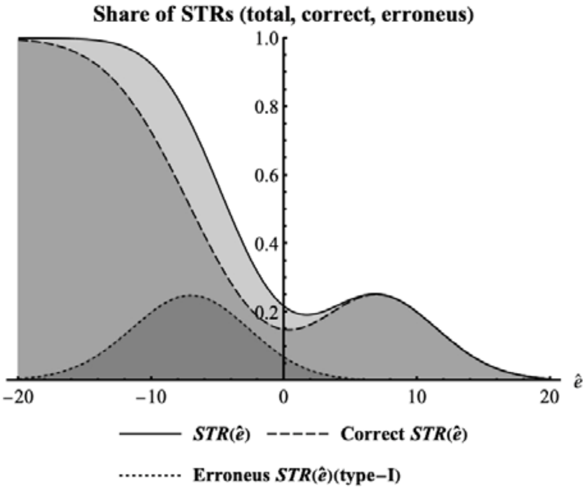


Figure 6 – STR activity

Figure 7 shows the $ER(\hat{e})$ and the incidence of type-I and type-II errors. As the plotted curves are derived assuming the usual parameters for the conditional probability distribution functions of the net evidence, the $ER(\hat{e})$ and the incidence of type-I and type-II errors in the figure are those associated with the underlying $MLR(\hat{e})$ represented in Figure 5.

[12] As usual, the curves in Figures 6 and 7 are derived assuming the usual parameters for the conditional probability distribution function of the net evidence. *S* is set equal to 1.

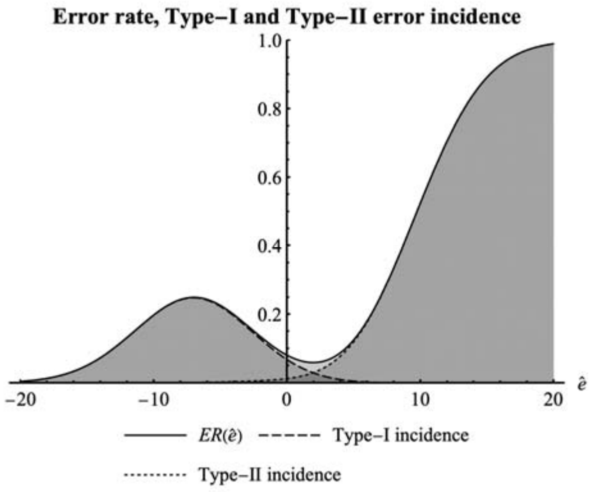


Figure 7 – Error rate and the incidence of type-I and type-II errors

2.6 Standard of evidence and maximum (possible) accuracy in STR activity

Ceteris paribus (given certain conditional probability distribution functions of the net evidence), for any given level of the standard of evidence, $\hat{e}$, different sanctions make the money-laundering activity more or less profitable. The money-laundering rate changes accordingly – the higher the sanction *S*, the lower the money-laundering rate $MLR(\hat{e})$ as well as the minimum money-laundering rate, $MLR_{min} = MLR(0)$. Figure 7 provides the money-laundering rates for different sanctions.

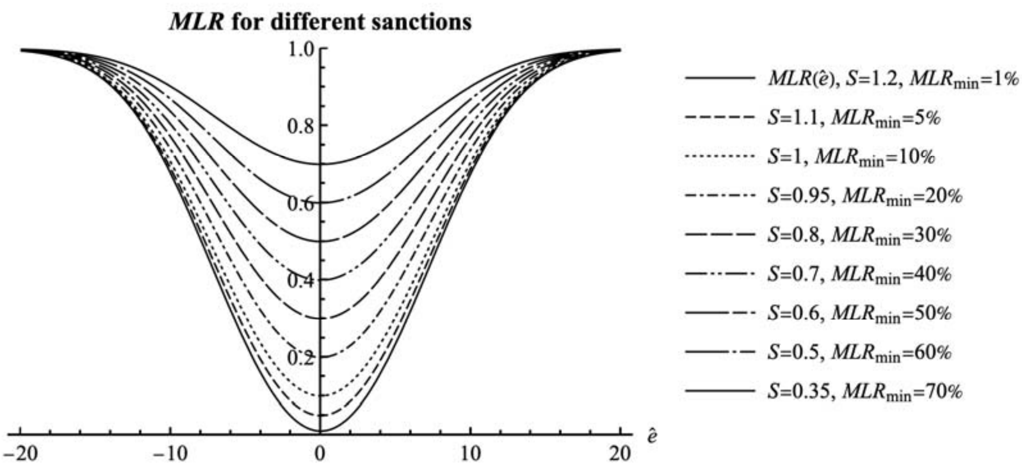


Figure 8 – Money-laundering rates for different sanctions

Given a certain standard of evidence, when the money-laundering rate increases because sanctions are decreasing, the STR activity also increases (*Figure 9*) and the incidence of type-

I errors decreases (Figure 10). This implies that the higher the money-laundering rate, the higher the share of correct STRs.

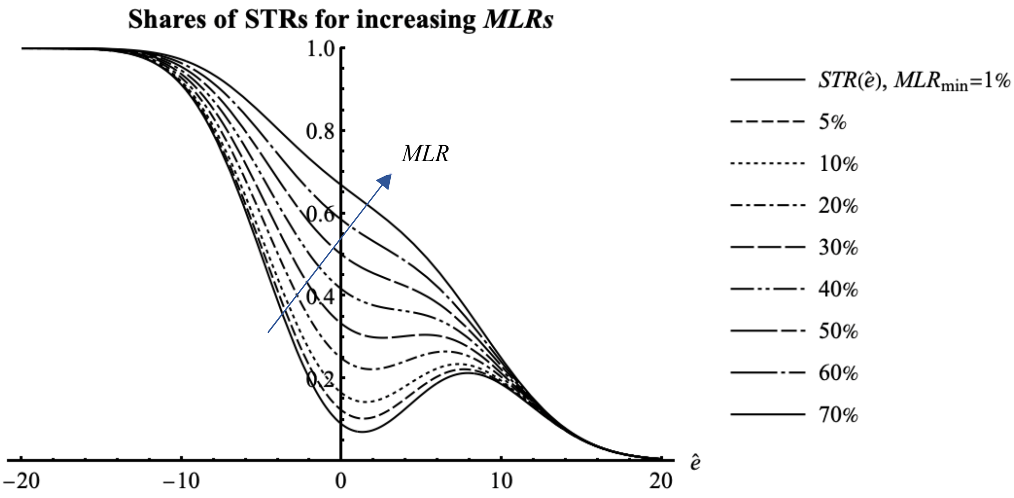


Figure 9 – STRs for increasing money-laundering rates

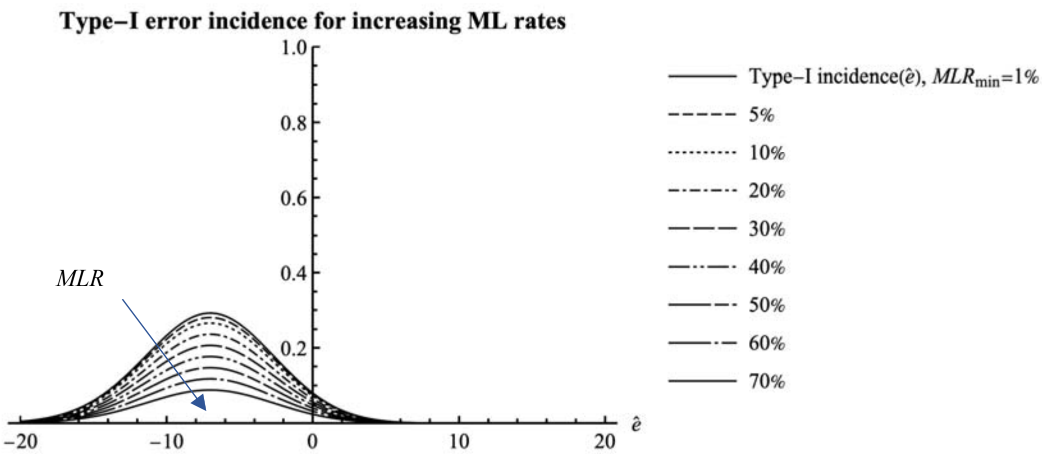


Figure 9 – Type-I error incidence for increasing money-laundering rates

In contrast to the incidence of type-I errors, given a certain standard of evidence, the incidence of type-II errors increases when the money-laundering rate increases, as shown in Figure 11.

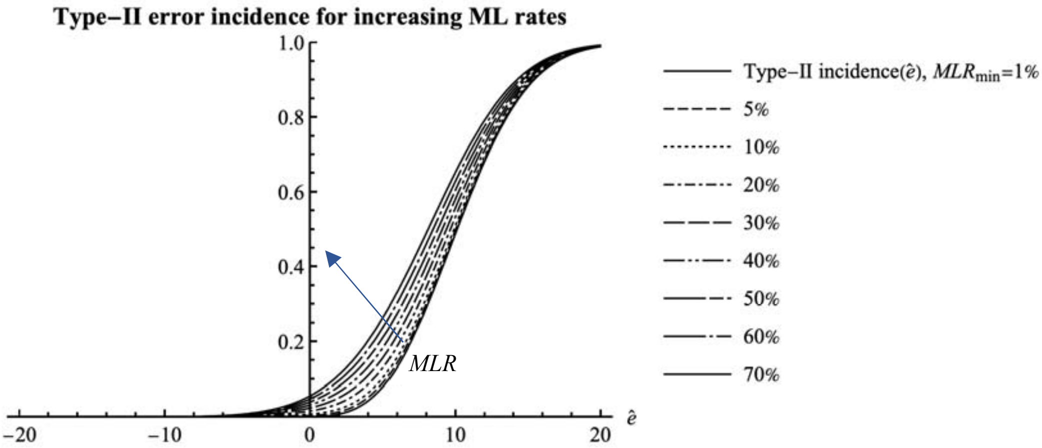


Figure 11 – Type-II error incidence for increasing money-laundering rates

In terms of the accuracy of the suspicious reporting activity as measured by the error rate $ER(\hat{e})$, note that intermediaries and professionals could minimize (nullify) the error rate by setting the standard of evidence to a sufficiently low level (see Figure 12). In fact, when the standard of evidence is very negative, the incidence of both type-I (Figure 10) and type-II (Figure 11) errors reaches zero.[13] However, this result is paradoxical and not desirable. On the one hand, reporting to the FIU on the basis of evidence indicating that the focal transaction is a regular one would not make sense. On the other hand, a very low standard of evidence zeroes out errors simply because the incentives to abstain from money laundering disappear. Therefore, money-laundering activity explodes (see Figure 8) and all of the transactions have to be reported as suspicious (no type-I errors; Figure 10). Indeed they are (Figure 9) thanks to the very low standard of evidence that is applied (no type-II errors; Figure 11).

For these reasons, the standards of evidence that should be analysed with respect to the accuracy of reporting activity are those in the neighbourhood of $\hat{e} = 0$. By zooming in on these values of $\hat{e}$, as we do in Figure 13, we find that the (local) minimum of the error rate (indicated by a cross) changes depending on the underlying money-laundering rate. As shown in Figure 13, the standard of evidence that (locally) minimizes the error rate decreases as the minimum money-laundering rate (MLR_{min}) increases.

In particular, when the money-laundering rate is such that its minimum $MLR_{min} > 0.5$, then the higher the MLR_{min}, the lower the standard of evidence that provides the most possible accurate reporting activity. Conversely, when the money-laundering rate is such that its

[13] All of these results can be derived analytically (see Dalla Pellegrina et al., 2020).

minimum $MLR_{min} < 0.5$, then the lower the MLR_{min}, the higher the standard of evidence that provides the most possible accurate reporting activity.

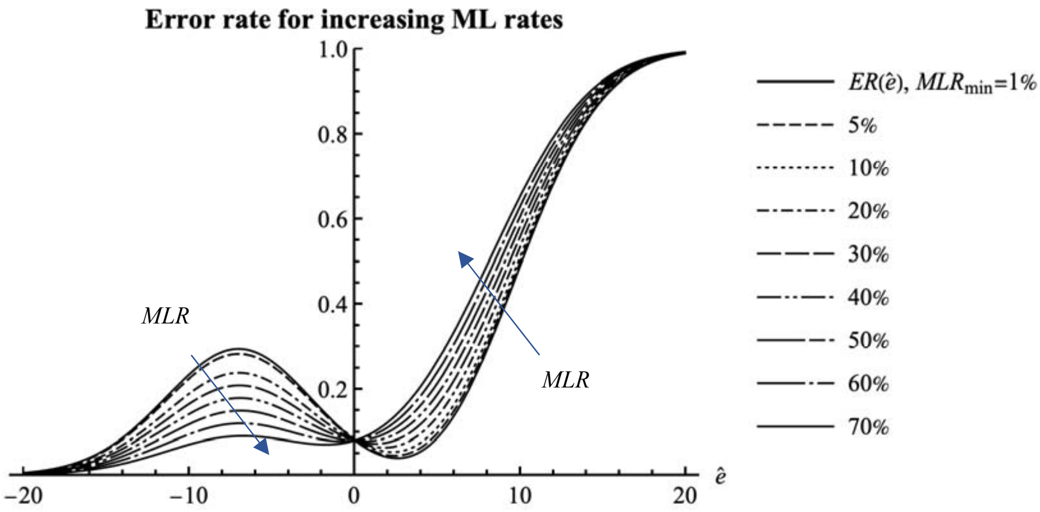


Figure 12 – Error rate for increasing money-laundering rates

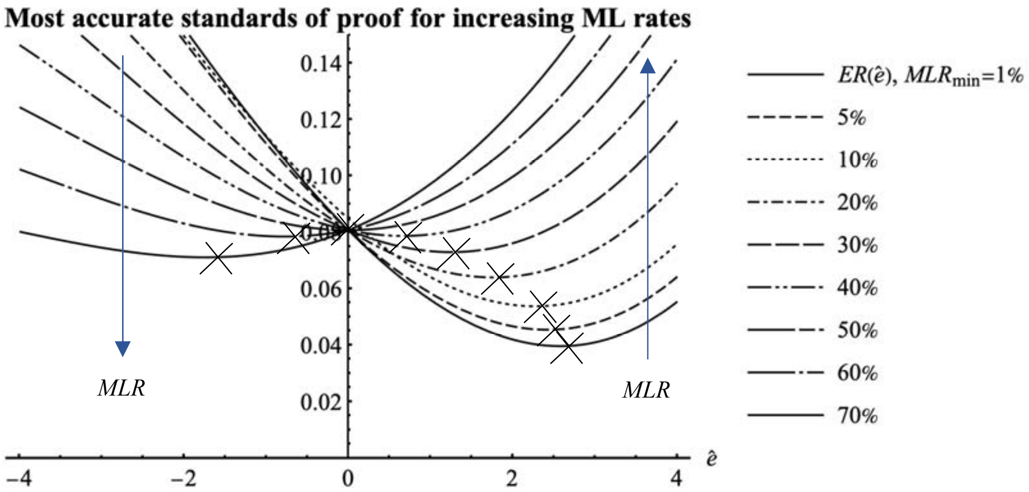


Figure 10 – Optimal standard of evidence for increasing money-laundering rates

RESULT 2: The standard of evidence that (locally) minimizes the error rate decreases as the minimum money-laundering rate MLR_{min} increases. In particular, when the money-laundering rate $MLR(\hat{e})$: $MLR_{min} > 50\%$, then the higher the MLR_{min}, the lower the standard of evidence, $\hat{e}$, needed to provide the most possible accurate reporting activity. Conversely, when $MLR(\hat{e})$: $MLR_{min} < 50\%$, then the lower the MLR_{min}, the higher the standard of evidence, $\hat{e}$, needed to provide the most possible accurate reporting activity. The standard of evidence that minimizes the error rate is $\hat{e}$ = 0 (i.e., the preponderance of evidence standard) only when MLR_{min} is 50%.

As illustrated by the model, intermediaries and professionals typically face a trade-off when setting their "standards of evidence" for reporting a transaction to the FIU as suspicious. While deterrence goals can be pursued by simply setting a preponderance of evidence standard ($\hat{e} = 0$), the accuracy of reporting depends on the level of money-laundering activity. Those intermediaries and professionals concerned with accuracy should reduce their standards of evidence with respect to the preponderance of evidence standard when money-laundering activity is intense. Conversely, they should increase the applied standards of evidence when money-laundering activity is not overly pervasive.

3. Empirical assessment

The purpose of this section is to assess the evolution of the quality of the reports received by the Italian FIU in order to minimize type-I and type-II in the STR process. That assessment is followed by additional considerations related to deterrence.

In particular, this empirical exercise aims to establish whether the model's main implications are supported by the empirical evidence using both multivariate analysis and the approach based on sufficient statistics. More specifically, the first part of the analysis is carried out using data at the provincial level. This allows us to account for geographical specificities that might characterize the incidence of both laundering and reporting activities (dalla Pellegrina, Di Maio, Masciandaro, & Saraceno, 2020). Due to data limitations,[14] we perform the second part of the empirical investigation on information at the (national) aggregate level.

First, we define the following empirical proxy for the standard of evidence, ($\hat{e}$):

$$\hat{e} = \frac{[ML\ police\ reports - STR] + |ML\ police\ reports - STR|}{source\ crimes}. \quad (7)$$

In the numerator, the first term in square brackets accounts for excess reporting activity to the FIU in a given province-year relative to the *true* incidence of money laundering (ML). Reporting activity is measured as the number of STRs submitted to the FIU by financial intermediaries, while the true incidence of the money-laundering crimes is represented by the number of police reports of money laundering.

[14] Data regarding STRs submitted to the FIU and dismissed STRs constitute the only publicly available information.

The rationale behind the choice of the difference between money-laundering police reports and STRs as a measure of excess reporting (the numerator of equation (7)) is that, ceteris paribus, an increase in STRs in relation to police reports can be interpreted as banks requiring less evidence on bank customers' suspicious transactions before reporting them to the FIU (i.e., a decrease in $\hat{e}$). Reasonably, and according to the data (see Table A1.1 in Appendix 1), the number of suspicious transactions reported to the FIU is greater than the number of police reports (as the latter is roughly a subset of the former). Therefore, the overall difference must be negative. For this reason, we sum the lowest (negative) value of the difference, in module, from the negative term in square brackets to avoid negative values in the numerator of (7). Source crimes are used in the denominator to normalize the excess reporting activity across provinces with different crime rates.

A challenging methodological aspect stems from the fact that we cannot directly observe the true incidence of money laundering because of its concealed nature. As criminal activities are part of an underground economy, the number of reports submitted to the authorities provides only partial insight into the overall phenomenon.

Notably, a relatively high number of reports in a given geographical area may provide contradictory indications. In particular, in order to validate the assumption that the number of money-laundering police reports is a good proxy for the latent fact, we must exclude the possibility that an increasing number of reports reflects either more efficient crime apprehension or higher sensitivity of citizens to criminal misconduct. While we do not have full information to address this issue, we have some evidence that supports this hypothesis. More specifically, the higher variability in money-laundering activity compared to both the variability of the efficiency of crime repression and the intensity of citizens' reporting activities in the Italian provinces supports the use of money-laundering police reports as a reliable measure of the incidence of money laundering (see Appendix 1).

For each Italian province, we collected information on police reports of both money laundering and source crimes on an annual basis. For source crimes, previous studies estimate that organized crime's highest-return activities are drug trafficking, prostitution, racketeering and counterfeiting (e.g., Abadinsky, 2010). In line with the broader literature (e.g., Draghi, 2007), we added the robbery and micro-crime indexes provided by the Italian National Institute of Statistics (ISTAT).

As there are several different types of source crimes, we performed a confirmatory factor analysis (Jöreskog, 1969) to obtain a unique, comprehensive measure of $\hat{e}$. This technique is useful to the extent that the frequencies of similar types of crime are correlated across provinces. Hence, reducing a number of source crimes to one or more latent factors simplifies the interpretation of the subsequent empirical analysis.[15]

Specifically, we constructed seven individual standard of evidence measures, one for each type of source crime. These measures have identical numerators but different denominators. We carried out a factor analysis on these individual measures in order to obtain a reduced number of factors as direct proxies for the standard of evidence ($\hat{e}$).

The data are from the Italian provinces and cover the time period from 2009 (corresponding to the introduction of the risk-based approach in Italy) to 2012.[16]

Table 11 – Factor analysis on source crimes, Italian provinces, 2009-2012

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	5.25326	5.09544	0.9747	0.9747
Factor2	0.15781	0.03504	0.0293	1.004
Factor3	0.12277	0.07352	0.0228	1.0268
Factor4	0.04926	0.08559	0.0091	1.0359
Factor5	-0.03633	0.02168	-0.0067	1.0292
Factor6	-0.05802	0.0413	-0.0108	1.0184
Factor7	-0.09931		-0.0184	1
LR test: independent versus saturated: $chi^2(21) = 3287.15$, Prob. > $chi^2 = 0.00$				
Number of observations		412		
Retained factors		4		
Number of parameters		21		

[15] Alternatively, we could have summed the number of police reports for the different types of crimes to construct a synthetic measure of source-crime activity. However, factor analysis helps give more weight to those source crimes that play a greater role in the money-laundering process (and, therefore, a better capacity to forecast the latent variable $\hat{e}$).

[16] We concentrate on the years immediately following the introduction of the risk-based approach. We have more recent data from the FIU, although this information is aggregated at the national level. We use it in the second part of the empirical analysis. However, our aim is to observe the effects of the introduction of the risk-based approach following the implementation of the first EU directive on this matter (Directive 2005/60/EC on the prevention of the use of the financial system for the purpose of money laundering and terrorist financing, Legislative Decree No. 231 of November 21). For this reason, we believe it is crucial to concentrate (at least in the first part of the analysis) on the years immediately after the introduction of the new legislation, as the adjustment process implemented by financial intermediaries and other reporting agents no longer requires an extended period of time and produce statistically significant effects. Amendments of the legislation have been introduced, which could interfere with the effects investigated in the paper.

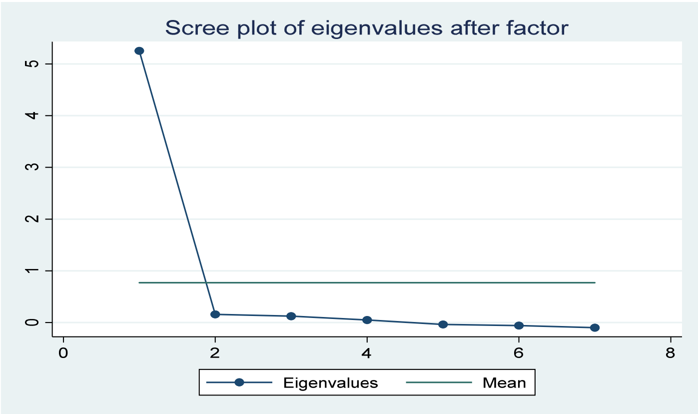


Figure 12 – Scree plot from factor analysis on source crimes, Italian provinces, 2009-2012

The results of the factor analysis are shown in Table 1 (additional details in Appendix 2). The corresponding scree plot presented in Figure 14 suggests the retention of a single factor that will represent a unique empirical measure of standard of evidence at the provincial level. We aim to analyse its evolution over time and its incidence on other measures in the model's setup.

The first step in assessing the model's ability to evaluate the effects of changes in the standard of evidence on type-I and type-II errors is to understand in which area of Figure 5 the data suggest setting the Italian situation in the years of interest. More precisely, we aim to formerly check the sign of the correlation between the standard of evidence measure just illustrated and the money-laundering rate, defined as *MLR* in the model, at the provincial level.

For this purpose, we ran a regression with *MLR* in province i in year t as a dependent variable and the standard of evidence, $\hat{e}$, as an explanatory factor:

$$MLR_{it} = \beta_0 + \beta_1\, Detected\_ML_{i,t} + \beta_2\, Real\ GDP_{i,t} + \beta_3\, Length\ criminal\ trials_{i,t} + \beta_4\, \hat{e}_{i,t} + \lambda_i + \mu_t + \varepsilon_{it}, \qquad (8)$$

where the subscript i refers to the province and t refers to the year. Given our empirical purposes, we measure *MLR* as the number of police reports of money laundering scaled by the amount of bank transactions (loans plus deposits). This measure, especially its denominator, reflects the share of transactions undertaken for money-laundering purposes in relation to the overall number of transactions. MLR_{it} is the money-laundering rate observed in the province in the 12 months preceding time t; λ_i and μ_t are province and time fixed effects, respectively; and $\varepsilon_{i,t}$ is an idiosyncratic error term clustered at the provincial level. The estimated sign of β_4

captures the positive correlation between MLR and our proxy for the standard of evidence.[17] We use provincial real GDP and two proxies for the efficiency of the detection mechanism (i.e., the share of detected money-laundering operations measured as the share of police reports with a known author relative to total money-laundering reports, and the length of criminal trials) as covariates. Summary statistics for these variables are available in Appendix 1. All variables are logged.

The regression output, which is obtained through linear estimation, is reported in Table 2 (upper panel). It suggests that Italy should be positioned on the right-hand side of the origin in Figure 5 (i.e., as $\hat{e}$ decreases, MLR decreases as well, and vice versa). Furthermore, to shed light on the reverse situation, Table 3 (Column (a)) shows that factor 1, as a proxy for $\hat{e}$, follows a substantially decreasing pattern in the period of interest.

For robustness, in the lower panel of Table 2, we report the regression output using an alternative proxy for $\hat{e}$. This is similar to the one reported in Equation (7) but with a different denominator (i.e., provincial GDP). This measure accounts for the possibility that money is not laundered locally.[18] The results have the same implications as those obtained using Factor 1.

Table 2 – Regression analysis, Italian provinces, 2009-2012

Dependent variable: $MLR_{i,t} = \frac{ML\ police\ reports}{volume\ of\ bank\ transactions}$	Coef.	Std. err.	t	P>|t|	[95% conf. interval]	
$\hat{e}$ = Factor 1	0.032	0.011	2.910	0.004	0.010	0.054
Detected ML	-0.016	0.011	-1.440	0.153	-0.039	0.006
Real GDP	0.021	0.048	0.440	0.661	-0.075	0.117
Length of criminal trials	-0.007	0.017	-0.400	0.690	-0.040	0.027
Constant	0.014	0.395	0.030	0.970	-0.763	0.791
Province fixed effects	Yes					
Year fixed effects	Yes					
Dependent variable: $MLR_{i,t} = \frac{ML\ police\ reports}{volume\ of\ bank\ transactions}$	**Coef.**	**Std. err.**	**t**	**P>|t|**	**[95% conf. interval]**	
$\hat{e} = \frac{[ML\ police\ reports - STR] + \|ML\ police\ reports}{GDP}$	0.261	0.087	3.010	0.003	0.089	0.433

[17] The regression analysis is not intended to estimate a causal relationship between the standard of evidence and the money-laundering rate. The sign of the correlation between the two variables only aims to provide an understanding of Italy's position in Figure 5.

[18] As we use the number of police reports of source crimes as a denominator, we implicitly assume that money can only be laundered locally (i.e., within a province's borders). To overcome this constraint, GDP is used as an alternative denominator to account for the possibility of conducting money laundering abroad and the possibility of importing laundering activities from other provinces.

Detected ML	-0.015	0.012	-1.300	0.197	-0.039	0.008
Real GDP	0.020	0.042	0.470	0.642	-0.064	0.103
Length of criminal trials	-0.004	0.015	-0.250	0.806	-0.033	0.026
Constant	0.129	0.105	1.230	0.220	-0.079	0.337
Province fixed effects	Yes					
Year fixed effects	Yes					

Notes.
OLS estimates. Variables are in natural logs (1 summed to each observed value in order to avoid negative values), except factor 1. Standard errors clustered at the provincial level in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Observations: 1,957. Number of provinces: 103. Unit of observation: province/year. Number of observations = 412. R-squared = 0.8687.

Given this evidence and in accordance with Figure 5, as the standard of evidence decreases (Table 3, Column (a)), the model suggests that: *i*) *MLR*, as a measure of deterrence, should decrease given the positive correlation between the standard of evidence and *MLR* along with a decreasing pattern of $\hat{e}$; *ii*) reporting activity (*STR*) has an indeterminate sign; and *iii*) the incidence of type-I errors should increase, while the incidence of type-II errors should decrease.

In order to test the model's predictions, we use the sufficient statistics approach pioneered by Chetty (2009) and recently applied to the study of money laundering by Imanpour et al. (2019). One useful feature of the model is that the variables of interest depend on only a few constructs that correspond to the real world and are easily observable in the available (mostly aggregated) data.

Table 3 – Patterns of ê, MLR and STR, Italian provinces, 2009-2012

Year	Standard of evidence ($\hat{e}$)(1) pattern in the period of interest	*MLR*(2) pattern in the period of interest	*STR*(3) pattern in the period of interest
	(a)	(b)	(c)
2009	1.222	0.120	0.258
2010	0.643	0.118	0.291
2011	0.226	0.118	0.319
2012	0.000	0.124	0.338

Notes.
(1) Equal to factor 1 (averaged by year).
(2) Measured as ML police reports/volume of bank transactions (at the national level).
(3) Measured as total STRs submitted to the FIU/volume of bank transactions (at the national level).

With regard to *i*), Table 3 (Column (b)) provides evidence on the stability of *MLR*. According to the model, *MLR* is around its minimum in the period of interest. In other words, deterrence is maximized (see Figure 5). From this, we infer that $\hat{e}$ is likely to be closer to the preponderance of evidence standard ($\hat{e} = 0$).

With regard to *ii*), we use the model's predictions (see Figure 6 and the evidence for *i*)) to make inferences about the pattern of reporting activity. In fact, although STRs are not monotonous for all positive values of the standard of evidence, an increase in reporting activity should be observed when $\hat{e}$ is decreasing and approaching the preponderance standard. This is confirmed by the growing number of STRs in relation to the volume of bank transactions in the observed period (Table 3, Column (c)).

Point *iii*) and Figure 6 also suggest that type-I errors are likely to increase on the area on the right-hand side of the origin (positive values of $\hat{e}$). We measure type-I errors as the ratio of the number of dismissed STRs to the total number of STRs submitted to the UIF. As reported in Table 4, after an initial drop (2009-2010),[19] this measure increases over time, basically returning to the level seen prior to the introduction of the risk-based regulation. Therefore, the model's predictions are again confirmed by the data.

Finally, given that there are no reliable proxies for type-II errors, we exclusively rely on and draw inferences from the model (Figure 7) to determine whether type-II errors increased in the period of interest. As data from the FIU cover a longer and more recent time span, we cautiously infer that as type-I error continuously increased until 2017, the opposite occurred with type-II errors.

Table 4 – Pattern of STRs, type-I and type-II errors (Italian provinces, 2009-2012); type-I and type-II errors, Italian provinces, 2010-2017

Year	Type-I error incidence (1)
2009	0.191
2010	0.095
2011	0.026
2012	0.049
2013	0.116
2014	0.227
2015	0.178
2016	0.108
2017	0.171

Notes: (1) Measured as STRs dismissed by the UIF/total STRs accruing to the UIF (at the national level).

4. Concluding remarks

[19] There could be several reasons for this initial pattern, which is not evident in Figure 6. One possibility is that the new regulation caused relevant changes in the data-collection and imputation procedures. Another is that the transposition of the new legislation led to delays in learning the new reporting procedures among financial intermediaries, causing an anomalous wave of STRs (a marked increase in the denominator).

The risk-based approach proactively involves financial intermediaries and other professionals in the AML system. These actors must establish risk-based procedures and criteria (the "know-your-customer" principle) for the reporting of certain transactions as suspicious to the FIU. From this perspective, the first level of the AML system can change the standard of evidence that is used to report a given transaction to the FIU.

The theoretical model proposed in this paper offers an interpretation of the behaviour of financial intermediaries and professionals with respect to two important goals: the deterrent effects of their reporting activities and the accuracy of those reports. We empirically assessed the model's main predictions using both multivariate techniques and sufficient statistics. The analysis, which was based on Italian data, concentrated on the role of financial intermediaries—the largest pool of actors submitting STRs to the FIU. We first tested the effects of the introduction of the risk-based methodology on type-I errors and on deterrence. Thereafter, we used sufficient statistics combined with the model's predictions to make inferences regarding the pattern of type-II errors and, consequently, accuracy.

The empirical outcome (using disaggregated data at provincial level) suggests that in the period of interest (i.e., in the years immediately following the introduction of the risk-based approach), financial intermediaries and professionals lowered the standard of evidence required to report a transaction as suspicious. The adoption of this "tougher" approach by the Italian intermediaries might have been motivated by the fact that these intermediaries are severely sanctioned if they do not report transactions that are subsequently detected as money-laundering transactions. With respect to the deterrence goal, the data combined with the model's predictions suggest that the standard of evidence actually applied was close to a preponderance of evidence standard and that MLR was at its minimum.

Furthermore, in line with the model, we use the sufficient statistics approach (Chetty, 2009). In this regard, we find that the observed increase in STR activity in relation to total bank transactions is reasonable due to the predicted decrease in the standard of evidence adopted by the intermediaries. The model predicts an increase in the incidence of type-I errors, which was confirmed by the data. This finding might relate to the fact that intermediaries and professionals are not formally punished for over-reporting. Conversely, we conclude that the incidence of type-II errors must have decreased in the period of interest – a conclusion that stems directly from the model. This is also motivated by the increase in the standard of evidence. In terms of policy, this inferred conclusion is particularly important, as data or proxies on the incidence of type-II errors are not easily observed at any layer of reporting activity.

Finally, although the risk-based approach aims to improve reporting quality, Italian authorities should be aware that although the MLR seems to be relatively stable (i.e., close to the maximum deterrence), the incidence of reporting errors is not at the minimum. In particular, while the inference about type-II errors is encouraging, type-I errors increased following the introduction of the new reporting rules. On the one hand, these aspects could be detrimental for a bank's reputation and client retention. On the other hand, the AML authorities are doing most of the job of managing type-I errors. In fact, the number of employees in the Italian FIU increased considerably in the period of interest.[20]

From a policy perspective, the emerging evidence seems to indicate that the risk-based paradigm is helpful in combatting money laundering, at least in Italy. However, false positives are still a major issue deserving of further consideration. Researchers may wish to apply the approach proposed in this paper to other contexts in order to understand where different countries are positioned in terms of the accuracy of the information transmitted to the FIUs and the deterrence of money-laundering activities.

[20] Between 2009 and 2012, the number of employees increased from 97 to 121. Given the high professional level of the FIU's employees, this increase is relevant. In 2018, the FIU had 146 employees (UIF, Annual Reports, 2010-2013, 2019).

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Appendix 1

We can use data in Table A1.1 to (at least partially) assess the legitimacy of using money laundering reported to the police in a given province as the numerator in our measure of money-laundering activity. Specifically, the ratio of the mean value of money-laundering police reports to its standard deviation is 0.56 (14/24.79). When we use the percentage of money-laundering reports with a known author as a proxy for the efficiency of crime repression, the ratio is 14.63 (58.67/4.01), which is much higher. The ratio of the mean value of source-crime police reports to its standard deviation can be used as an inverse measure of the volatility of citizens' reporting activity. This ratio is 0.60 (1,863/3,107), which is not as supportive as the previous evidence. However, in light of the former evidence, we are reasonably confident that reports of money-laundering crimes are likely to serve as a fairly good measure of criminal infiltration in the legal economy.

Table A1.1 – Summary statistics, Italian provinces, 2009-2012

Variable	Source	Frequency of observation	Unit of observation	Mean	Std. dev.	Min.	Max.
Source-crime police reports(1) (2)	Italian National Institute of Statistics (ISTAT, hereafter)	Yearly	Number	1,863	3,107	21	23,060
ML police reports(2)	ISTAT	Yearly	Number	14	24.79	0	165
Source crimes with known offender(2)	ISTAT	Yearly	%	58.67	4.01	49.00	88.00
Bank loans(3)	Bank of Italy	Yearly	EUR million	25,260	68,797	958	712,398
GDP (real value added, at 2010 price level)(2)	ISTAT	Yearly	EUR million	13,603	19,995	1,649	158,148
ML crimes with known offender(2)	ISTAT	Yearly	%	70.25	18.64	0	100
Length of criminal trials	Ministry of Justice	Yearly	Days	327.41	95.73	133.86	588.5

Notes. Obs. 412.

(1) Police reports refer to the number of crimes reported to the Police Authority.

(2) Total inflows in the 12 months prior to the observation.

(3) Observed at the end of each period.

Appendix 2

Table A2.1 – Factor loadings, Italian provinces, 2009-2012

Factor loadings (pattern matrix) and unique variances					
Variable	**Factor1**	Factor2	Factor3	Factor4	Uniqueness
Prostitution	**0.6703**	0.2698	0.1045	0.0360	0.4656
Racketeering	**0.8972**	0.0039	-0.1629	-0.1075	0.1569
Counterfeiting	**0.8156**	0.1345	-0.1017	0.0811	0.2999
Drug trafficking	**0.9575**	-0.0674	-0.1055	0.1054	0.0565
Robberies	**0.9260**	-0.0023	-0.0211	-0.1201	0.1276
Micro-crime index 1	**0.8448**	0.0026	0.2364	-0.0383	0.2290
Micro-crime index 2	**0.9197**	-0.2497	0.0867	0.0531	0.0814

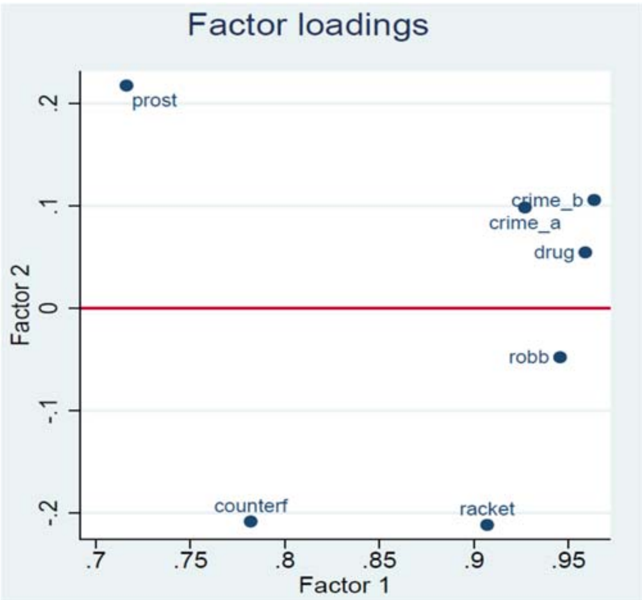

Figure A2.1 – Correlations between factor loadings, Italian provinces, 2009-2012