Beyond blacklists: an alternative approach to rating countries at high-risk of money laundering

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The paper addresses the issue of how the risk of money laundering (ML) at country level can be measured. A number of official blacklists and grey lists exist, issued by national and international organisations such as FATF, European Commission or US INCSR, which rank countries according to their (presumed) ML vulnerabilities and regulatory weaknesses. But these lists may be biased by geo-political influence, and are not supported by empirical evidence. This paper suggests a new approach for operationalising and assessing the risk that a country may attract illicit proceeds. It develops a composite indicator of ML risk, which builds on the inputs from previous criminological literature. It then validates the indicator against observed evidence of ML by employing a unique dataset of 2818 individuals involved in ML cases. The analysis shows a strong correlation between the new indicator and empirical evidence of ML, but a null (and sometimes negative) correlation with official AML blacklists. The work advances the current understanding of ML determinants, and empirically demonstrates the importance of *proximity, opacity* and *security* in driving illicit proceeds. It proposes that a unique, and universally valid, measure of high-risk countries is not appropriate for explaining a relational phenomenon like money laundering. It also provides empirical ground that may help to revise the current AML blacklisting process, and minimise its unintended consequences such as de-risking.

Keywords: money laundering; risk; blacklists; FATF; proximity; indicator.

1. INTRODUCTION

On June 17th, 2020, Commerzbank was fined 38 million pounds by the UK Financial Conduct Authority due to violations in anti-money laundering (AML) and countering terrorist financing (CTF) controls. Among other offences, the regulator identified that *"40 high-risk countries were missing"* from the bank's AML transaction monitoring tool (FCA, 2020). In recent years, many other financial institutions were fined several million US dollars for conducting financial transactions with countries which appear on official AML/CTF blacklists issued by some national or international organisations. In some instances, institutions were forced to close local branches and correspondent banking relationships in the identified high-risk countries as a way to mitigate the probability in incurring these fines. A process ordinarily referred to as *de-risking* effect (Ramachandran et al., 2018; Nance & Tsingou, 2020).

Given the intended and unintended consequences produced by these rankings of high-risk countries on banks, firms, citizens and whole economies, official AML/CTF blacklists have been widely questioned by scholars, NGOs and sometimes by governments themselves, at least the black/grey listed ones. Three main critiques have been moved: (i) that the criteria underpinning the inclusion in AML/CTF blacklists are methodologically flaw; (ii) that they are not always fully transparent; (iii) that they may be geo-politically biased, in the sense that tend to penalize countries which are not fully aligned with the 'Western bloc' (Ferwerda & Reuter, 2020; Halliday et al., 2019; Littrell & O'Brien, 2019; Ferwerda, Deleanu & Unger, 2019; Levi et al., 2018; Riccardi & Milani, 2018; van Duyne & van Koningsveld, 2017; Sharman, 2009).

However, scholars have not been able to go beyond criticism and propose good alternatives. The only exceptions are represented by the methodologies proposed by some researchers linked with advocacy groups like Tax Justice Network, whose *Financial Secrecy Index* and *Corporate Tax Haven Index* (Tax Justice Network, 2020) have become quite popular among AML/CTF researchers and practitioners (although not being specifically related to money laundering). However, these lists have not been tested against any evidence of money laundering and financial crime, apart from selected case studies taken from journalistic investigations such as Panama Papers or Paradise Papers. The lack of empirical support raises doubts whether these alternative rankings are better – in the sense of closer to the actual ML/TF activities – than official blacklists themselves.

This paper addresses this issue. It contributes to the debate on high-risk jurisdictions in the AML/CTF domain by proposing a novel methodology for assessing the money laundering (ML) risk of a country. It develops a country-level indicator of ML risk which is based on the inputs stemming from both the economic and the broader criminological literature. Then, it empirically applies the new methodology to one country (Italy) and validates it against observed evidence of transnational money laundering activity carried out by more than 2800 Italian individuals.

This research has important research and policy implications. First, in terms of research, it introduces a novel perspective to the study of ML risk, conceptualised as a relational phenomenon. It assumes that the risk of destination countries (countries *j*) is a function of their relationship with the country where the illicit money originates from (country *i*). The implication of this is that one single, universally valid, list of high-risk countries does not exist; rather, there will be as many lists of high-risk *j*-countries as there are *i*-countries.

Second, it contributes to the relative dearth of empirical literature currently on ML/TF. It provides confirmation to the importance of *proximity* in driving flows of criminal money (Kruisbergen et al., 2015, 2019; Steinko, 2012; Petrunov, 2011; Ferwerda, van Saase, et al., 2019): paraphrasing Reuter (1983), if *small is beautiful* for illegal enterprises, then *close is beautiful* in money laundering. It also confirms the role as a ML vulnerability of *opacity*, intended in terms of cash-intensity and corporate secrecy, as well as *security*, which pertains to the stability and reliability of the economic, financial and regulatory system of destination countries. The analysis also provides empirical evidence that supports the hypothesis that high levels of corruption are a cost in ML activities, and that low taxation does not necessarily attract criminal proceeds.

Third, the analysis employs new databases and innovative techniques to operationalise complex phenomena that are otherwise difficult to observe. For the first time in criminological research (at least in ML), the Lexis Nexis WorldCompliance dataset is extensively used.

The topic addressed by this paper is also of central importance to ongoing debate on high-risk countries fostered by media investigations, such as the *Panama Papers, Paradise Papers* and *Russian Laundromat* (to mention only a few). It goes beyond anecdotal evidence by providing hard data which demonstrates that some Western countries have the same or even higher level of ML vulnerability than offshore and exotic jurisdictions. And, as it pertains to Italian criminals at least (including Italian mafias), European (and especially EU) states are much more appealing than Caribbean islands as places to move dirty money to.

By proposing a risk assessment methodology which is transparent, replicable and validated (both from the technical and empirical perspective), this paper can help to support the revision of the current blacklisting process (of FATF, the EU and other national and international organisations), and to mitigate the unintended consequences deriving from both the de-risking phenomenon and the international isolation of (presumed) risky jurisdictions. Finally, this paper contributes to debate around the issue of *illicit financial flows*, which, in turn, is at the centre of one of the United Nations (UN) Sustainable Development Goals (SDGs), namely SDG 16.4.

The paper is organised as follows. Chapter 2 provides a review of the literature on, first, the concept of ML risk; and, second, the main determinants of ML risk across countries. Chapter 3 illustrates the employed methodology and data sources, also describing how the ML determinants reviewed in the previous section can be operationalised into variables and a model. Chapter 4 shows the results of the application of the model to one country (Italy) and elaborates on the main findings. Chapter 5 discusses the research and policy implications of the performed analysis.

While referring in various sections to AML/CTF regime, the paper focuses almost exclusively on financial flows geared towards laundering the money and not, for example, those aimed at either reinvesting the money in the same (or other) predicate offences or funding terrorist activities. I will therefore refer solely to ML (and ML risk) and not to terrorist financing, which ordinarily follows different strategies, has different drivers and, as such, would warrant a wholly separate investigation. [1]

2. LITERATURE REVIEW: MONEY LAUNDERING RISK AND DETERMINANTS

2.1 Money laundering risk

Over the course of the past twenty years the risk-based approach (RBA) has become the cornerstone of the global AML regime. FATF Recommendation No. 1 and its Interpretative note suggest that activities aimed to prevent and trace ML should be *"commensurate with the risks identified"* (FATF, 2012, p. 31): higher risks require enhanced measures, lower risks allow for more simpler ones.

[1] Obviously, a clear-cut distinction between ML and terrorist financing (TF) is not always possible. ML actors and terrorists may share *modi operandi* of money transfers and investments, as well as converging interests in illicit markets , and, at a higher level, they at times share ideologies and recruitment channels (Weisburd et al., 2020). For a review of similarities and differences between ML and TF see C. Walker (2018).

Underpinning the RBA is the concept of ML risk. This follows the same rationale of the classical risk management literature – see the ISO standard 31000 or Rausand (2013). In its assessment guidelines (FATF, 2013), the FATF defines ML risk as a combination of two elements: (i) the *likelihood* that a ML (or terrorist financing) event will occur; (ii) the *consequences* (which the FATF adopts as a synonym for impact) it could generate. In turn, the likelihood (L) that an event will occur is determined by two further dimensions, which the FATF designates as *threats* (T) and *vulnerabilities* (V).

A threat is defined by the FATF as any *"person or group of people, object or activity with the potential to cause harm to, for example, the state, society, the economy, etc."* (FATF, 2013, p. 7). In other words, threats correspond to all those people or activities that produce illicit proceeds and/or that may need to launder money. For example, drug trafficking groups that have accumulated dirty proceeds need to launder them. Therefore, threats are often related to ML predicate offences, or, as put by the International Monetary Fund (IMF), *"a threat is largely related to the nature and scale of potential demand for ML"* (Dawe, 2013, p. 112). Ultimately, then, it can be defined as the factor that generates the need for money to be laundered.

A vulnerability can be defined as any circumstance or factor which attracts, facilitates, or allows threats to occur. Or, in the words of the FATF, any factor which *"may be exploited by threats"* (FATF, 2013, p. 7). This could involve, for example, high levels of banking secrecy or the presence of *"weaknesses in prevention of, detection of and/or enforcement against money laundering events"* (Ferwerda & Reuter, 2018). Similarly, according to the IMF, vulnerabilities refer to *"intrinsic properties in products, services, distribution channels, customer bases, systems, structures and jurisdictions (including weaknesses in systems, controls or measures)"* (Dawe, 2013, p. 113).

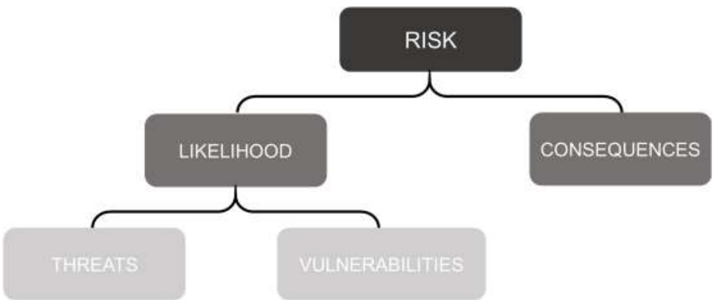
The function of threats, vulnerabilities and consequences yields the risk, which can then be expressed as:

$$R = f(L; C)$$

Where

$$L = g(T; V)$$

Figure 1 – Money laundering risk according to the FATF



Source: Author's elaboration of FATF (2013)

Under this formulation, threats, vulnerabilities, and consequences are assumed to be wholly independent from each other, and therefore can be identified and measured separately. This is a pretty radical (albeit useful) simplification proposed by the FATF, which, in reality, does not hold up. Interactions between threats, vulnerabilities and consequences occur; and both conceptualization and measurement problems for all the three factors arise (see Savona and Riccardi, 2017, for a review).

In particular, as indicated by Ferwerda and Reuter (Ferwerda & Reuter, 2018, 2020), threats typically influence the level of acceptability of vulnerabilities. In the AML domain, the opposite tends to dominate, that is, vulnerabilities influence threats. In a country where, ideally, criminals would be immediately detected, i.e. a country that had no AML weaknesses – the same authors note – there would be no threat. Or, phrased otherwise: *"the threat will be slight as a consequence of the prevention effect of AML* *policy"* (Ferwerda & Reuter, 2018, p. 5). These considerations have to be taken into account when discussing the concept of ML risk *applied to countries*.

2.1.1 Money laundering risk of a country

How do we apply this conceptual framework to a country? In other words, how do we define countries *as being at high-risk of money laundering*? According to the FATF definition cited above, a high-risk country, from the perspective of ML, would be one that is characterised by a high likelihood of ML events occurring, and which would suffer hugely from the occurrence of these ML events. This would be countries that are characterised by high *threats*, high *vulnerabilities*, and high *consequences*. To make it even more concrete, this is countries with a high volume of illicit proceeds (generated domestically or abroad) that are ready to be laundered, and which are characterised by weaknesses in both their social, economic, financial, institutional fabric and their AML prevention, detection and enforcement system, which not only makes it more likely that illicit proceeds will be laundered, but also makes the impact of ML more significant.

At this point, the problems mount. First, what does it mean when we say that a country suffers great ML consequences? How can this be operationalized and measured? The identification and measurement of ML consequences is a never ending debate with poor empirical evidence in support (see Ferwerda, 2013, for a review). Paradoxically, empirical evidence is much stronger with respect to demonstrating the negative consequences of AML activities than of ML itself, at both the local (e.g. Slutzky et al., 2020) and global level (Morse, 2019; Halliday et al., 2019; Ramachandran et al., 2018). As a result, consequences are usually left outside any model. This is what most national ML/TF risk assessments (NRAs) do, the same EU supranational risk assessment (SNRA) does, and the FATF itself suggests: *"countries may opt to focus primarily on […] understanding threats and vulnerabilities"* (FATF, 2013b, p. 8). In other words, the risk assessment becomes an evaluation of the *likelihood* of ML only.

Then, there is the problem of the interplay between threats and vulnerabilities. The endogeneity of threats with respect to vulnerabilities highlighted by Ferwerda and Reuter (2018, 2020), and discussed above, applies, above all, when ML is carried out across countries. Countries with high ML vulnerabilities may also attract foreign (or external) ML threats. This generates situations in which countries only witness illicit proceeds that come from abroad – or at least this is what they declare. The NRA of Switzerland, for example, reports that the country had almost no internal ML threats, and that they were mainly external (CMGF Switzerland, 2015, pp. 31–32).

Therefore, a narrower perspective could be adopted, in which 'high-risk' countries are characterised by high vulnerabilities only – i.e. by so many weaknesses in their social, economic, financial and regulatory domain, which not only facilitates the laundering of domestic illicit proceeds, but also attracts dirty money generated abroad. Implicitly, this is what most – basically all – existing measures and blacklists of ML risk (from official AML/CTF blacklists, to the Tax Justice Network indicators) assume. They are assessments of *"weaknesses", "lack of [something]", "strategic deficiencies", "secrecy factors"* - and so on, to use their own words. Even when these measures declare that they account for threats (as the FATF ratings state), they are, in fact, focusing only on vulnerabilities. In other words, the likelihood of ML could become solely a function of vulnerabilities: vulnerabilities raise ML threats or, when thinking in terms of countries, *attract* threats.

$$R = f(V)$$

Eventually, a country is at risk depending on its capacity to *attract* (or retain) illicit proceeds, rather than to *generate* them. Before illustrating precisely what these vulnerabilities are, two further important assumptions have to be stated.

First, the endogeneity does not mean necessarily that countries' vulnerability towards ML is independent from threats. Some jurisdictions, for example, may be vulnerable to certain ML threats, but not to others. Let us imagine that there are two groups of drug traffickers active and operating in Spain: a Colombian one (specialising in cocaine trade) and a Moroccan one (specializing in hashish). It is likely that the Colombian group will eventually try to transfer (either in full or in part) its proceeds back to Colombia, as will the Moroccans attempt to do to Morocco (as the judicial cases analysed by Steinko, 2012, demonstrate). In other words, from the perspective of the same origin country *i*, i.e. Spain, Colombia and Morocco are both countries at high-risk of attracting illicit proceeds, but the first is only so in relation to Colombian money, while the second is only at risk of the dirty money generated by Moroccan groups. This example – but many others could be done - makes it clear that the nature, nationality, goals, opportunities and constraints of the ML offender and of the predicate offence – i.e. of the ML threat - influence the likelihood that criminal proceeds leave the country, and may also determine the destination of the money – and therefore the level of ML vulnerabilities of the destination country, and ultimately its ML risk.

The second consideration pertains to the fact that different countries may be equally at risk, but in different types or stages of money laundering. For example, some may be at high-risk in relation to *layering* (e.g. they are good places to incorporate shell companies); others in regards to *placement* (e.g. they are good places to open bank accounts to deposit dirty money); others may be at high-risk of *transit* (e.g. for round-tripping of the illicit money); and others represent an ideal final destination for the dirty money to subsequently be integrated via, for example, investing in real estate, and so on. This has an impact on their vulnerabilities. For example, if a country is used for establishing an intermediate shell company, then corporate opacity could be a more important vulnerability than, say, the level of cash intensity.

2.2 Determinants of money laundering across countries

It is important now to understand what these ML vulnerabilities – or *determinants*, *attractiveness* factors, or *pull factors* - are. For doing so, a review of the literature in this field is carried out.

Most previous studies have taken a classical economic approach to ML, stressing the role that countries' structural socio-economic characteristics play as drivers of international ML flows. An example of this approach is the *gravity model* introduced by Walker (and Unger) in the late 1990s, which, in fact, was an adaptation of the model commonly used to study international trade introduced by Tinbergen (1962). Gravity models in the ML domain assume that cross-border illicit flows follow (a sort of) Newton's law, i.e. are driven by the mass of the countries (usually, the size of the economies) and their distance (in geographic, cultural and economic terms). The function is further intermediated by other attractiveness factors (see Ferwerda et al., 2012; Ferwerda, van Saase, et al., 2019 for a review).

The gravity approach has achieved a certain degree of success in empirical research on ML, and has been adopted in various analyses of a variety of direct and indirect proxies of illicit financial flows. For example, to detect anomalous portfolio investments (Gullo & Montalbano, 2018), anomalous cross-border corporate ownership connections (Aziani et al., 2020), or to explain flows of money related to suspicious transaction reports (STRs) (Cassetta et al., 2014; Ferwerda, van Saase, et al., 2019). Undoubtedly, drivers related to international trade play a critical role in explaining cross-border illicit financial flows. But the ML literature does not explain why this happens. This, in turn, has led to a big mystification: that criminals involved in ML respond to the same utility functions as multinational firms or of countries involved in global trade, despite the fact that there is abundant evidence confirming that this is not the case. Even large and structured criminal organisations that have some corporate patterns, such as certain mafia-type cartels, do not act like Nike or Google when laundering money.

It is necessary instead to better understand why and how criminal actors move their illegal money across countries. In other words, understanding why and how ML threats (the criminals) exploit ML vulnerabilities. This means examining those studies which have investigated the objectives and unique characteristics of the criminal actors involved in ML. Ultimately, it is necessary to going beyond the classical economic approach to ML, and discover (or rediscover) the contribution that criminological literature could bring to the study of ML. If this broader approach is taken, then the set of determinants of ML activity across countries – i.e. the vulnerability of a country attracting illicit proceeds – could be simplistically grouped in three families: (i) proximity, (ii) opacity and (iii) security.

2.2.1 Proximity

When talking about ML across countries, *proximity* can refer to the geographical, cultural and economic closeness between the place where the predicate offence is committed/the illicit money was generated/the criminal actor is based (or comes from) and the place where the money is laundered. The role of proximity as a driver of ML is one of the most evident recurrences in empirical works, case-studies, police reports, and judiciary files in the AML/CTF field. Surprisingly, it remains one of the most neglected and underestimated factors when talking about ML across territories. Conversely, the argument that 'due to globalisation and technology, illicit money could move everywhere' has been much more successful (see e.g. Europol, 2017, p. 36) – but, in fact, is supported by much weaker evidence.

Proximity emerges in numerous works. In their analysis of around 1,200 individual assets of (suspected) participants in OCGs identified by Dutch authorities, Kruisbergen et al. showed that 82.1% of these properties (real estate, businesses, other items) were located either in the country of origin (62.5%) or in the country of residence (19.6%) of the criminals (Kruisbergen et al., 2015). In Finland, Petrell and Houtsonen conducted a similar analysis of assets seized from organised crime, concluding that most of them were located in Finland – with the exception of a few assets in neighbouring countries – Russia, Estonia and Sweden (Petrell & Houtsonen, 2016). Steinko (2012), who analysed 367 cases of ML judged between 1995 and 2011 in Spain, concluded that out of the total, only 23 (6.2%) involved an international dimension, which, in most cases, however, amounted to *"not much more than a zig-zagging transfer between several financial institutions"* (Steinko, 2012, p. 914). And, in any case, he showed that the most frequent foreign country mentioned as a receiver of money was Colombia, which was the country of origin for most of the predicate offenders involved in the cases (cocaine traffickers), followed by European countries. The analysis conducted by Transcrime on the assets confiscated from Italian mafias found that these assets were almost exclusively located in Italy; and, more specifically yet still, within those regions and provinces in which the presence of mafia groups was the highest (Transcrime, 2013). This was valid for both real estate properties (Dugato et al., 2015) and firms (Riccardi, 2014; Riccardi et al., 2019).

These findings of course may be biased by two things. First, the proven incapacity of law enforcement agencies and judicial authorities to trace and seize criminal assets abroad, outside their jurisdiction. Second, that most of the mentioned studies refer to organised crime groups which may be more prone to launder closer to their area of activity than other offenders like corrupt politicians or tax fraudsters (see below). But the 'proximity' paradigm is also confirmed by some available statistics on STRs, which usually do not focus on organised offenders only. In Italy and the Netherlands, only a minor share of STRs concern foreign countries; when it happens, most STRs refer to bordering jurisdictions (e.g. Germany, Luxembourg and Belgium for the Netherlands; Switzerland for Italy) or countries with strong communities active in the country (e.g. China for Italy; Turkey for the Netherlands). In Italy, an analysis of the Italian FIU showed that only 3% of the STRs received by the local FIU in 2012-2013 concerned financial transactions involving high-risk foreign countries which in any case were European jurisdictions (Gara & De Franceschis, 2015, p. 20). In Peru, foreign countries were identified in only 14.2% of the STRs received by the local FIU during the period between 2015-2018 (UIF Peru, 2020). And, on average, 93% of the individuals identified in STRs were Peruvian.

Why is proximity so important for money laundering? Some scholars, inspired by international trade theory, attributes the reason to the lower transportation costs (Walker & Unger, 2009). Some answers could be found in the extensive literature on organised crime (OC) infiltration in the economy. If OC invests in the economy also to expand its control and grip on the territory and on the market (Arlacchi, 1983; Graebner Anderson, 1979; Jacobs et al., 1999; Levi & Soudijn, 2020; Transcrime, 2013), then proximity ultimately makes this instrument much more effective.

Proximity can also be viewed as a form of insurance for the tenure of criminal associations involved in ML and their predicate offences. Moving illicit proceeds far away from where the predicate crime was committed (and where criminals are likely to have a stronger presence) may require opening the criminal association up to additional individuals and organisations (e.g. couriers, intermediaries, advisers, professionals) and expose the group to risks of tip-offs, leaks, fraud, arrests and seizures. This can be seen as an implication of the 'illegal enterprise theory': the risky and uncertain market conditions faced by criminals tend to limit the number of partners and employees involved (Bouchard & Morselli, 2014; Malm & Bichler, 2013). If *small is beautiful* for criminals, then, staying (and laundering) close is the best way to remain small. Reuter did note this already in his 1983 book: *"For a variety of reasons illegal enterprises can be expected to be local in scope, not to include branches in remote locations. Perhaps the most significant reason is the difficulty of monitoring distant agent performance"* (Reuter, 1983, p. 127). This can be expanded in terms of cultural proximity. Adapting social embeddedness theory (Kleemans & van de Bunt, 1999; Varese, 2011), ML offenders could rely on social and cultural proximity to 'embed' and secure their dirty money.

Finally, another reason may be related to the cash-nature of illicit proceeds. Despite the evolution of predicate offences and ML techniques, criminal activities are still very much cash-intensive (Kruisbergen et al., 2019; Soudijn, 2018; Riccardi & Levi, 2018 for a review). Laundering where the proceeds were generated, or in close territories at a reasonable driving distance, could ease the moving of dirty cash, minimising losses, seizures and arrests – and transportation and storage costs.

All these inputs from the literature appear to point towards the same conclusion: *ceteris paribus*, the closer - geographically, linguistically, culturally - the destination country, the higher its risk from a ML perspective.

2.2.2 Opacity

The role played by *opacity* as determinant of ML has been also stressed by a vast array of scholars and institutions. Criminals employ various layering techniques, which make it difficult to trace the money back to its illicit origin and to their beneficial owners. Specifically, opacity can be disaggregated in terms of (a) payment opacity, (b) banking secrecy and (c) corporate opacity.

Opacity in payments is related to the possibility of maintaining anonymity vis-à-vis the scope, origin, and beneficiary of a financial transaction. Traditional bank transfers, cheques, digital payments (such as e-money), but also cryptocurrencies, do not offer full anonymity, both because various information must be declared typically, and because these transactions usually require prior entry within the financial system (e.g. the opening up of a bank account), and, as such, are subject to preliminary AML due diligence. The most anonymous means of payment remains cash. While most criminal markets remain cash-intensive, cash is (still) the most frequently used ML technique worldwide (Europol, 2015; Riccardi and Levi, 2018). Most AML STRs have to do with anomalous cash-use, deposits and withdrawals: for example in Europe they account for 40% of all those issued annually, according to Europol (2017). In countries with higher levels of cash-intensity (i.e. with a higher use of cash for payments), it is easier to integrate illicit proceeds into the legitimate economy, and the risk of ML is also higher.

Second, the possibility to maintain anonymous bank accounts and the lack of obligations in keeping banking records – better known as *bank secrecy* – has been deemed as an important ML vulnerability by numerous scholars and institutions (Blum et al., 1999; Levi, 2018). While in recent years bank secrecy has generally decreased, recent investigations and media scandals – such as the *FinCEN files* or the *Troika Laundromat* – have confirmed the role played by vulnerable banking systems in facilitating illicit money flows.

But the most important facet of opacity is probably *corporate secrecy*. Legal persons are often used as veils to conceal the identity of beneficial owners and the illicit origin of the funds, and, as demonstrated by a wide literature, criminals tend to opt for jurisdictions in which they can easily hide company information, especially that which pertains to ownership and financials (van der Does de Willebois et al., 2011; van Duyne & van Koningsveld, 2017; Knobel, 2019; Findley et al., 2020). The establishment of beneficial ownership registers may only partially solve the problem, as criminals will continue to employ figureheads and exploit asymmetries across countries. Scholars have stressed that it is not only important *who* controls a firm, but *how* they do so (Riccardi & Milani, 2018; Joaristi et al., 2018). Recent works, based on analyses of several million firms' links worldwide, demonstrated empirically the relationship between anomalies in corporate ownership and evidence of illicit activity (Aziani et al., 2020; Garcia-Bernardo et al., 2017; Jofre et al., 2020).

2.2.3 Security

The 'illegal enterprise theory' applies to ML offenders, too: they operate in a highly unstable and unregulated environment, and must adopt extra safeguards to protect their activities (Levi & Soudijn, 2020): contracts are not enforceable in courts, assets need to be concealed in order to avoid seizure from law enforcement, the risk of tipping off by banks, professionals and other AML obliged entities should be minimised. This mean that ML offenders must strike the right balance between the need to hide their proceeds, on the one hand, and, on the other hand, to make sure that the proceeds remain accessible and secured. *Ceteris paribus*, among jurisdictions with the same level of opacity, criminals will invariably opt for those that provide the best assurance that funds will remain at their disposal. Opacity – without accessibility – is an insufficient condition for successful ML: crime profits must be enjoyed eventually.

This is why strong economies and financial systems represent good potential destinations for illicit money. The size of a country's economy has always played a role in gravity models applied to illicit financial flows (e.g. Walker & Unger, 2009; Gullo & Montalbano, 2018; Aziani et al., 2020). It represents the equivalent of *mass* in Newton's theory, but it also facilitates the camouflaging of the investment: *"hiding money is easier in a bigger pool of money"* (Ferwerda et al., 2019, p. 10).

Similarly, the stability of regulations and governments is an important pull factor, as it would guarantee higher safety of criminals' personal assets. It may appear contradictory - why would criminals seek out a well-run country? – but empirical evidence seems to support this hypothesis: Ferwerda and colleagues (2019), in their analysis of STRs, demonstrated that political violence is negatively correlated to ML (the more violent the country, the less attractive it is for illicit proceeds); Aziani and colleagues (2020) find a positive correlation between rule of law and the amount of anomalous financial flows.

This brings to corruption. Do high levels of corruption in a country favour or disincentivise those seeking to launder illicit proceeds? The literature is deeply ambiguous about this relationship (see Chaikin & Sharman, 2009 for a review). But while some scholars argue that it is easier to find ML facilitators in highly corrupt countries, others provided some empirical evidence on corruption being a protective factor against ML (Walker, 1999; Aziani et al., 2020)

2.2.4 Other determinants

There are two other factors which recur occasionally in the literature as drivers of ML across countries: the first is (low) taxation; the second is profitability. In both cases the hypotheses are abundant, the empirical evidence is low.

Most of the countries with high levels of banking/corporate secrecy also offer fiscal advantages. This does not mean that low-tax rates are necessary for attracting criminal proceeds. In 2004, the US State Department and CIA declared that *"low-tax jurisdictions do not attract a disproportionate share of dirty money"* (Mitchell, 2002). However, neither the US nor the FATF have ever been vocal supporters of anti-tax-haven campaigns. With the exception of selected case studies, empirical evidence on the relationship between low taxation and money laundering is almost absent. Aziani et al. (2020) found no significant correlation between anomalous cross-border corporate ownership links and tax rates. Ferwerda et al. (2019) similarly found no correlation between suspicious ML flows (as reported in STRs received by the Dutch FIU) and the tax rate of the destination country. Gullo and Montalbano (2018) found a positive correlation between tax levels and anomalous portfolio investment annual flows, i.e. that higher tax countries attract, *ceteris paribus*, more anomalous investments than lower-tax regimes: *"in practice, all else being equal, a destination offering more secrecy and less controls is usually preferred to one with lower taxes"* (Gullo & Montalbano, 2018, p. 20).

With respect to profitability, the implications are more or less the same. Empirical evidence about profitability being a strong driver of ML is currently weak, both at the *micro* (firm) and *macro* (country) level. Moreover, problems of reverse causality may arise, as the attraction of illicit proceeds can drive economic and financial development – as the impressive GDP growth in recent years of some 'suspicious' jurisdictions (such as Malta) can suggest.

2.3 Research questions

Having defined the concept of ML risk, how this can be applied at the country level, and having discussed the ML vulnerabilities stemming from the extant literature, it is worth asking whether there is room to develop a new measure of ML risk at country level which could:

(i) be closer to FATF conceptual framework;
(ii) better incorporate the inputs proposed by the current literature, and;
(iii) be validated by empirical evidence.

To address this question, this paper develops an indicator of ML risk which heavily builds on criminological literature, and embed the three sets of identified vulnerabilities - *proximity, opacity* and *security*. The indicator will be tested in one country (Italy) and compared with observed evidence of ML activity so as to check its capability to detect (and predict) actual ML risk.

Also, the new ML risk indicator is compared to official AML blacklists (the FATF ones and the US INCSR list of 'major money laundering countries') and other measures of (presumed) ML evidence, namely the evidence stemming from media investigations (like Panama Papers) and other indicators such as Tax Justice Network's FSI and Basel AML Index.

3. METHODOLOGY

This section illustrates the methodology employed to construct the new indicator of ML risk at country level. First, it discusses the rationale behind the new measure (paragraph 3.1), the methodological approach (3.2), and finally how ML determinants are operationalized, with which data and sources (3.3).

3.1 Rationale

Defining ML risk as the capacity of a country to attract illicit proceeds implies attributing money laundering (or the *risk* of money laundering) a relational nature. The relationship is between a country *i*, where illicit proceeds come from (it can be called *origin* country), and other countries *j*, which attract these proceeds and for which the risk will be assessed (*destination* country). From the perspective of country *i*, high-risk countries are those countries *j* with a greater ability to attract proceeds from country *i.* In other words:

$$R_{ij} = f(V_{ij})$$

Where R_{ij} is precisely the risk of country *j* (from the perspective of i); *V* refers to the set of vulnerabilities associated with country *j* from the perspective of *i*. Vulnerabilities have the *ij* subscript as they are not only intrinsic features of the country that attracts the money, but are also a relational pattern that links country *i* with *country j*. Or, phrased otherwise, country *j* has a certain level of risk, not only because of its own characteristics, but also because of its peculiar relationship with country *i*.

The vulnerabilities included in the risk function are identified with the three categories discussed in section 2.2: *proximity*, *opacity*, and *security*. The function of risk could thus be rewritten as follows:

$$R_{ij} = f(P_{ij}, O_j, S_j)$$

Where P_{ij} includes measures of proximity between country *i* and *j*; O_j is a set of variables that measures the opacity of country *j*; and S_j is a set of variables that measures the level of security in the same country *j*. In other words, country *j* would be at greater risk (from the perspective of *i*), if it were closer to *i*, and if it had a higher level of *opacity* and *security*. While it is difficult to designate all of these features as 'vulnerabilities', the assumption being made here is that, all other things being equal, they ultimately make a country more 'vulnerable' from the perspective of ML.

Before looking at how these three risk dimensions are operationalised, it is worth stressing one important implication of this model: there will not be one single, and universally valid, list of high-risk countries. This is because the risk of any country *j* is ultimately a function of its relationship with country *i*. A list of high-risk countries exists solely *from the perspective of country i*. Therefore, there will be as many rankings of high-risk countries as there are countries *i* that exist.[2]

Another point to stress here is that this function models in a simplistic way the ML flow between the origin and destination country: money produced in *i* moves to *j* where it is subsequently laundered. As has been well-established in previous cases and literature, certain (probably a minority) of ML schemes rely on more complex round-tripping movements, involving conduit jurisdictions and *"throughflow countries"* (see e.g. Ferwerda et al., 2019). Countries *j* (destinations) could just as soon become countries *i* (origin) in the same ML process. However, to discern all these steps is almost impossible for most ML cases. Resultantly, the model I adopt here does not distinguish between a country acting as a conduit and another one acting as the end point for the integration of the dirty money: both are classified as the destinations of the illicit funds (i.e. countries *j*).

3.2 Methodological approach

The novel measure created is a composite indicator. Composite indicators are statistical tools which enable researchers to describe quantitatively a concept through its measurable components (OECD & JRC, 2008). They are widely used to represent 'unmeasurable' (at least through direct observation) phenomena, and to describe complex, multi-dimensional and sometimes elusive phenomena (see Bandura, 2006). This is why they have become also popular in the field of organised crime (e.g. van Dijk's, 2007; Dugato, De Simoni & Savona, 2014; Ganau & Rodríguez-Pose, 2017; Dugato et al., 2019), corruption (e.g. Transparency International's CPI; World Bank Control of Corruption index; Fazekas, Tóth, & King, 2013; Ferwerda, Deleanu, & Unger, 2016) and, more recently, in the assessment of ML risk (Riccardi, Milani and Camerini, 2018; Hopkins & Shelton, 2018; Ferwerda and Kleemans, 2018).

The methodology adopted here follows exactly these latter works, which in turn built on OECD guidelines (OECD & JRC, 2008). In particular, I follow an approach in seven (6+1) steps:

1. *Specification of a theoretical framework:* with identification of both the concept to be assessed and the risk dimensions to be covered by the indicator. This was discussed in Section 3.1 above;
2. *Operationalisation:* transformation of the identified risk dimensions into proxy variables so that they can be measured;
3. *Data collection, cleaning and organisation,* including imputation of missing data and standardisation;
4. *Multivariate analysis,* through the use of dimensionality reduction techniques to understand the underlying structure of the data and identify the latent components. In this case, I employ principal component analysis – PCA (see Appendix for details);
5. *Weighting and aggregation of extracted components* for producing the composite indicator;

[2] Obviously, one could generate a single indicator by computing the average or the sum of all the indicators across *i* countries for each *j*. However, this ranking will ultimately be a function of *i*-country-specific lists. This could also be a further direction of research, as discussed in the conclusions.

6. *Technical validation:* sensitivity analysis and robustness check to control whether results are robust and not depending on changes in the parameters of the analysis (e.g. weighting criteria, employed standardisation techniques, PCA rotation techniques etc).

Here, I introduce a further step:

7. *Empirical validation,* by correlating of the composite indicator with other ML risk measures and empirical evidence.

Empirical validation is what OECD designates as *"links to other indicators"*, a phase that aims to *"correlate the composite indicator (or its dimensions) with existing (simple or composite) indicators as well as to identify linkages through regressions"* (OECD & JRC, 2008, p. 21). For the purposes of this research, the empirical validation was carried out in two ways:

(a) By comparing the newly created indicator to other existing measures of ML risk (following Littrell and O'Brien, 2019);
(b) By testing the relationship of the newly created indicator, through correlation and regression analysis, with observed measures of ML activity.

With respect to (a), I compare the indicator with: (i) AML/CTF official blacklists and grey lists, namely FATF blacklists in both the 2000-2006 and 2008-2020 period, FATF scores of Technical Compliance and Effectiveness and the US INCSR in the 2008-2020 period; (ii) Tax Justice Network's Secrecy Score and Financial Secrecy Index (in their latest, 2020, version); (iii) the Basel AML index (latest 2019 version); (iv) Walker's attractiveness index (2009); (v) the country rankings as emerging from Panama Papers (2016), Paradise Papers (2017) and Russian Laundromat (2017). Details on how these measures of ML risk are calculated and normalised are provided in Appendix.

With respect to (b), the validation is performed in a specific country, Italy.[3] Specifically, I test the hypothesis that there is a positive and significant correlation between the indicator of high-risk countries (from the perspective of Italy) and the distribution of observed ML activities of Italian individuals across foreign countries (i.e. other countries than Italy). In other words, I test the significance of the coefficients of the following regression:

$$y_{ij} = ML\_cases_{ij} = \beta_0 + \beta_1[ML\_index_{ij}] + \beta_2 W_j + \varepsilon_{ij}$$

Where:

i = Italy ;

j =1,…,J countries with $j \neq i$;

$y_{ij} = ML\_cases_{ij}$ = number of cases of *ML* of proceeds originated from country *i* (i.e. Italy);

$ML\_index_{ij} = f(P_{ij}; O_j; S_j)$ is the composite indicator constructed with a set of variables that measure *proximity, opacity*, *and security* (see above);

W_j = a set of control variables, in particular, the size of country *j* and a variable that measures the magnitude of the potential predicate offences associated with ML conducted in country *j*.

Several variations of the model above illustrated, and different functional forms, were tested, including a version employing as explanatory variables the three components taken separately. For more details see Analysis below.

[3] Italy is chosen because of various reasons. First, because of the well-known power of its mafias, which still play a crucial role in transnational markets and which represents important ML actors on the global scene. Second, because of the size of the illicit proceeds generated in Italy, which make it a suitable origin country (or supplier country) of ML activities. Third, in Italy I could access a unique dataset of ML cases which was then used for the empirical validation (see here below), while, conversely, this data was not available for other jurisdictions.

3.3 Operationalisation, data and sources

The three identified sets of vulnerabilities – *proximity, opacity and security* – are further broken down in the sub-dimensions listed in Table 1, and then operationalised as illustrated in Table 2 and discussed below.

Table 1 – ML Vulnerability dimensions and sub-dimensions of country-level ML risk

Proximity (between *i* and *j*)	Opacity (of *j*)	Security (of *j*)
Geographical proximity	Payment anonymity	Economic size
Cultural proximity	Corporate opacity	Financial size
Monetary proximity		Regulatory stability

Source: Author's elaboration

Table 2 – Operationalisation of the variables used for constructing the composite indicator and for validating it

	Sub-dimension	*Variable*	*N. Obs*	*Mean*	*Std.dev.*	*Source*	*Year*
Proximity	Geographical proximity	*distance_rec*	208	.0004	.0006	CEPII	2017
		contiguity	207	.024	.154	CEPII	2017
	Cultural proximity	*comm_language*	193	.119	.147	CEPII	2017
	Monetary proximity	*comm_currency*	208	.111	.314	CEPII	2017
Opacity	Payment opacity	*cash_supply$_j$*	182	.320	.392	CIA and World Bank	2017
	Corporate opacity	*complexity*	97 (240) [b]	1.281	1.179	Crime&tech on Bureau van Dijk data	2018
		unavailability	97 (240) [b]	1.146	1.107	Crime&tech on Bureau van Dijk data	2018
	Banking secrecy	*Not operationalised*					
Security	Economic size	*GDP*	206	3.89e+11	1.69e+12	World Bank	2017 and 2014-18
	Financial size	*bank_credit*	225	55.32	39.24	World Bank	
	Regulatory stability	*rule_law*	214	.534	.229	World Bank	
	Ease of doing business	*procedure_to_start*	236	7.133	2.791	World Bank	
ML evidence	Observed money laundering cases	*ML_cases*	243	6.97	21.2	Author's elaboration of Lexis Nexis World Compliance	1995-2020[b]
		ML_cases_population	213	2e-04	1e-03		
	Associate/ predicate crimes	*other_crimes*	243	2.12	8.11		

Notes: [a] Not used when developing the indicator in Italy; b originally, included 97 observations (i.e. countries), 240 after imputation of missing values. Years: it refers to the last available year (LAY), used in the reference model of the PCA. In the case of 'Security' variables, PCA was run on 2017 data, but in the sensitivity analysis also a model with 2014-2018 average was calculated. :[b] 80% of the observations in the 2014-2020 period; 90% in the 2013-2020 period; 96.3% between 2010 and 2020.

Source: Author's elaboration of various sources

3.3.1 Operationalisation of proximity

Geographical proximity is operationalised using two variables that are commonly employed in gravity models: the contiguity between two countries (*contiguity*), i.e. a dummy signalling if countries share the same border (CEPII); and the physical distance (measured in km) between the population-weighted centres of the countries (CEPII). With respect to the latter, I calculate the reciprocal of the original distance (*distance_rec*) in order to ease interpretation in the PCA (i.e. the higher the number, the closer the countries). *Cultural proximity* is operationalised using a variable (*comm_language*), provided by CEPII, which measures the percentage of the population in *j* that speaks the same language as people in *i* (as in Aziani et al., 2020; Ferwerda, van Saase, et al., 2019; J. Walker & Unger, 2013). *Monetary proximity* is operationalised via a dummy variable (*comm_currency*) that indicates if two countries have the same official currency (e.g. France and Italy both have the euro), which is again provided by CEPII.

3.3.2 Operationalisation of opacity

Payment anonymity is measured by employing a proxy for money supply (*cash_supply*). Previous literature that measured the cash-intensive nature of a country or region used the so-called cash-ratio, i.e. the fraction of total daily payments made in notes and coins (Ardizzi & Iachini, 2013; Transcrime, 2018). Unfortunately, this proxy is only available for EU member states (as calculated by Transcrime, 2018). Therefore, I measure it with the ratio between the value of the money supply M1 (stock) on GDP. This variable has three advantages over other metrics: (a) it can be created from public data; (b) it encompasses a much larger amount of countries; (c) it not only takes into account the circulating notes and coins, but also other forms of liquid assets, such as demand deposits and bank accounts. Therefore, the stock money M1 not only enables researchers to capture the risks related to cash payment transactions, but also those related to the placement of liquidity in the financial/bank system.[4]

On the other side, I decide not to operationalise – and therefore to measure - *Banking secrecy*, because of the lack of appropriate variables, especially of a non-statutory nature. Overall, there is a lack of good measures of banking secrecy in extant literature, and, indeed, those studies which are similar to this paper also opted not to employ them.[5]

Similarly, *Corporate secrecy* was not measured using the scores offered by the FSI. Instead, I employ two variables which are the country-specific versions of two metrics, which have recently been developed at the firm level (for 380 million firms worldwide) by Transcrime (see Jofre, et al., 2020). The first variable (BOC – *business ownership complexity*) measures the degree of anomaly in firms' ownership structure, namely the average number of steps between a firm and its beneficial owners (so-called 'BO distance') compared to its peers (firms in the same sector, location and with similar size).[6]

[4] To further validate this variable, it was correlated against the ratio of World Cash Report currency in circulation on GDP. The correlation was positive and significant (.56), despite the low number of observations.

5 The FSI measures this dimension in a component (the KFSI1) which, in turn, is itself an indicator of six sub-components that include, among other things, (i) the consequences of breaching banking secrecy; (ii) compliance with FATF Recommendation 5, as evaluated by the FATF; (iii) the existence of duties on banks to report large transaction amounts; (iv) the existence of sufficient powers to obtain and provide banking information upon request. Beyond being questionable in their essence (at least with regards to some), these sub-components are also aggregated with discretional weights. Therefore, I ultimately decided not to use the KFSI1.

[6] A firm would have a distance = 1 if its beneficial owner (or all its beneficial owners) directly controlled the firm; distance = 2 if the control were exercised through another intermediate shareholder; distance = n if there were (n-1) intermediate shareholders between the firm and the beneficial owners, and so on. If a firm had more than one beneficial owner, then the average distance

The raw version of this measure was also employed in previous studies (Riccardi & Milani, 2018; Transcrime, 2018; Ferwerda & Kleemans, 2018). For the purposes of this analysis, I use, for each country *j* under analysis, the percentage of firms that fell within the class with the highest level of anomaly (i.e. BOC score = 5).[7] The second variable (BOU – *business ownership unavailability*) measures the percentage of ultimate beneficiaries in a corporate ownership structure, which are trusts, fiduciaries, foundations, mutual/investment funds and other corporate vehicles and do not allow for the identification of a beneficial owner – a natural person. For the purposes of this paper, for each country *j* I use the percentage of firms that fell within the highest risk class, which concerns those firms for which it is not possible to identify a beneficial owner for at least 50% of the nodes at the highest level of the corporate chain. [8]

3.3.3 *Operationalisation of* security

This dimension measures both the size of a country's economic and financial sector, and its regulatory stability. *Economic size* was proxied through GDP (in US dollars, at current prices). It is the most traditional measure of mass, which is why it is frequently employed in gravity models (Ferwerda et al., 2012, for a review). *Financial size* is measured with *bank_credit,* which is the ratio between the value of the overall bank credit to the private sector and GDP (both provided by the World Bank), which could be interpreted as the degree of specialisation within the financial industry. *Regulatory stability* was proxied (as in Aziani et al., 2020) through the Rule of Law index developed by the World Bank as part of its Governance Indicators (*rule_law*).[9] A variable that measures the number of procedures required by country *j* to start up a firm is also employed, but it will not be taken into account with the final model.

3.3.4 Operationalisation of ML evidence

As aforementioned, a measure of observed ML activity across countries is used to empirically validate the new indicator of ML risk. The validation is conducted in Italy, and employs a unique dataset which has hitherto not been used in ML-related research: the Lexis Nexis WorldCompliance (WoCo) dataset. This database is one of the most widely used, at the global level, for customer due diligence in AML and other KYC purposes by banks and other obliged entities.[10] It includes more than 2.5 million detailed profiles (of individuals and firms) at the global level and enables users to detect individuals, organisations and vessels linked to more than 50 risk categories, including so-called 'Sanctions', 'Enforcement', 'Adverse media', and others.[11] For each individual and firm included in the dataset, WoCo provides a textual summary of the reason for their inclusion, their links to the original source and a set of other information (e.g. country and date of birth, name of the institution or journal linked to the source) (see Appendix for an example). Starting from the WoCo dataset, I created a variable counting the

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among all its BOs was computed. For the purposes of the calculation, beneficial owners were identified using the 10% of the capital share as thresholds at any level of the corporate ownership.

[7] Country scores were calculated on a random sample of 5 million firms (mostly limited companies) to which Transcrime had access through Bureau van Dijk's ORBIS database. For European countries, Transcrime calculated these scores for around 15 million firms. Results were highly correlated (between .8 and .9 depending on the variants).

[8] To cite an example: let us hypothesise a company that has three ultimate beneficiaries, i.e. three nodes at the last level of the corporate ownership chain: one of them is a natural person, two of them are foundations which do not declare their beneficial owners. The unavailability score for this firm would thus be 66.6%, and therefore the company would fall into the risk class 5. Now let us assume that a country *j* has only two companies registered. These two firms would fall under risk class 2. The value of the country-*j* variable ***unavailability*** would be equal to 50% (i.e. half of the firms registered).

[9] For the purposes of this exercise, and to facilitate its interpretation, the original version (ranging from approx. -2.5 to 2.5) was normalised into a 0-1 scale.

[10] See https://risk.lexisnexis.com/global/en/products/worldcompliance-online-search-tool/

[11] 'Sanctions' refer to a list of specifically designated persons or entities in US OFAC, EU, United Nations and national sanction lists; 'Enforcement' to persons/entities named in official documents issued by the police, judicial authorities, FIUs and other public authorities in relation to arrest, prosecution or conviction for a certain crime; 'Adverse media' concerns persons/entities which are mentioned in the news and open sources in relation to arrests, prosecution or conviction. If a person appears in more than one category, only the most relevant one is reported in the dataset according to the WoCo hierarchy, which, for these three categories, is the following: (1) Sanctions; (2) Enforcement; (3) Adverse Media.

number of times foreign countries (different from Italy) were mentioned in cases involving Italian individuals who were either arrested, prosecuted or convicted due to ML (see Appendix for details).

Overall, the resulting dataset comprises 2818 Italian individuals, 80% of whom were arrested/prosecuted/convicted between 2014 and 2020. In the dataset, there are 3092 mentions of countries being involved in ML activities (i.e. 3092 individual-country pairs): 45.2% of them referred to Italy; and 54.8% referred to foreign countries. Specifically, 75 foreign countries are mentioned, along with Italy (the analysis presented in Section 4 will elaborate and provide more details on this).

It is important to note that the construction of this variable suffers from some weaknesses. For example, whenever other offences beyond ML are mentioned in regards to a specific case or person, it is not always possible to understand, from the available sources, if they are the predicate offences which generated the illicit proceeds, or crimes committed by the individual in other contexts or time intervals. Therefore, it would be more appropriate to designate them as *associated offences* as opposed to *predicate* offences. Second, it is not always possible to trace the time series of the ML scheme, nor of the criminal process the individual had undergone. Available dates are seemingly provided at random, sometimes referring to an event (e.g. an arrest, a conviction, a seizure), other times to the issue date of the media report. For this reason, I chose not to conduct any time series analysis, while I took this dataset as a 'stock', based on the assumption that no relevant change over time could be observed in the strategy of Italians willing to launder their dirty money abroad.

4. ANALYSIS

This section illustrates the results of the indicator of ML risk developed for *i*=Italy, which denotes only those countries which are at high-risk from the perspective of Italy. Eventually, a ML risk score is calculated for 164 j-countries (with j ≠ i = Italy). Generalising the results from Italy to other countries is not wholly appropriate precisely because of the relational nature in which ML risk has been conceptualised. However, considering that the vulnerabilities related to the dimensions O (*opacity*) and S (*security*) are *i*-irrelevant, i.e. they are intrinsic features of *j*-countries, the analysis of these variables can be generalised to any *i*-country.

4.1 Principal component analysis (PCA)

Table 3 below presents the correlation matrix for the identified variables. Most of the proxies employed are generally positively and significantly correlated. In particular, the variables that denote *proximity* are correlated both among each other and those that measured *security*. Corporate opacity variables (*complexity* and *security*) are correlated between each other and slightly with *cash_supply*. Following the same approach proposed by extant literature (Jolliffe, 2002), I drop from the PCA those variables that were not significantly correlated with most of the other variables. This should have been the case for GDP and procedures to start a business. The first is kept in order to maintain coherence with gravity models and to act as a control; the second is dropped not only because of the low correlation, but also because it was assessed to not be a proper measure of security, but rather of efficiency. Two further models (without GDP and with procedures to start a business) are presented in the sensitivity analysis (see below). Overall results do not change.

Table 3 – PCA: Correlation matrix

	contiguity	*distance_rec*	*comm_language*	*comm_currency*	*cash_supply*	*unavailability*	*complexity*	*GDP*	*bank_credit*	*rule_law*	*procedures_to_start*
contiguity	1										
distance_rec	0.6***	1									
comm_language	0.402***	0.496***	1								
comm_currency	0.354***	0.510***	0.449***	1							
cash_supply	0.142*	0.349***	0.275***	0.399***	1						
unavailability	0.141**	0.272***	0.305***	0.39***	0.306***	1					
complexity	0.076	0.037	0.277***	0.186***	0.174**	0.529***	1				
GDP	0.033	-0.021	0.068	0.029	0.062	-0.044	-0.093	1			
bank_credit	0.260***	0.280***	0.407***	0.327***	0.307***	0.141*	0.052	0.198***	1		
rule_law	0.235***	0.311***	0.516***	0.433***	0.331***	0.261***	0.221***	0.187***	0.695***	1	
procedures_to_start	-0.073	-0.069	-0.168**	-0.173**	-0.068	-0.068	-0.172**	-0.014	-0.234**	-0.411***	1

*Notes: *, **, *** significant at 90%, 95% and 99% confidence level respectively. N.obs. range from 173 (*cash_supply *and* comm_language*) to 222 (*proced_ to_start *and* bank_ credit*)*

Source: Author's elaboration of various sources

The table below reports the results of the PCA after employing an orthogonal rotation of the three identified principal components (PCs), using Varimax rotation strategy as recommended by most literature.

Table 4 – PCA. Matrix of rotated components (Varimax)

N.Obs	164	
N. Comp	3	(N<*Q*)
Rho	0.645	
KMO test	0.77	

Component	Variance	Difference	Proportion of overall variance	Proportion of model variance	Cumulative
PC1	2.42	.37	24.2%	37.5%	37.5%
PC2	2.05	.06	20.5%	31.8%	69.3%
PC3	1.99	.	19.9%	30.7%	100%

Variable	PC1 *'Proximity'*	PC2 *'Security'*	PC3 *'Opacity'*	Unexplained
contiguity	0.59			.289
distance_rec	0.61			.200
comm_language	0.34			.399
comm_currency	0.33		0.22	.396
cash_supply		0.21	0.23	.671
unavailability			0.62	.259
complexity			0.65	.269
GDP		0.53		.514
bank_credit		0.58		.301
rule_law		0.54		.248

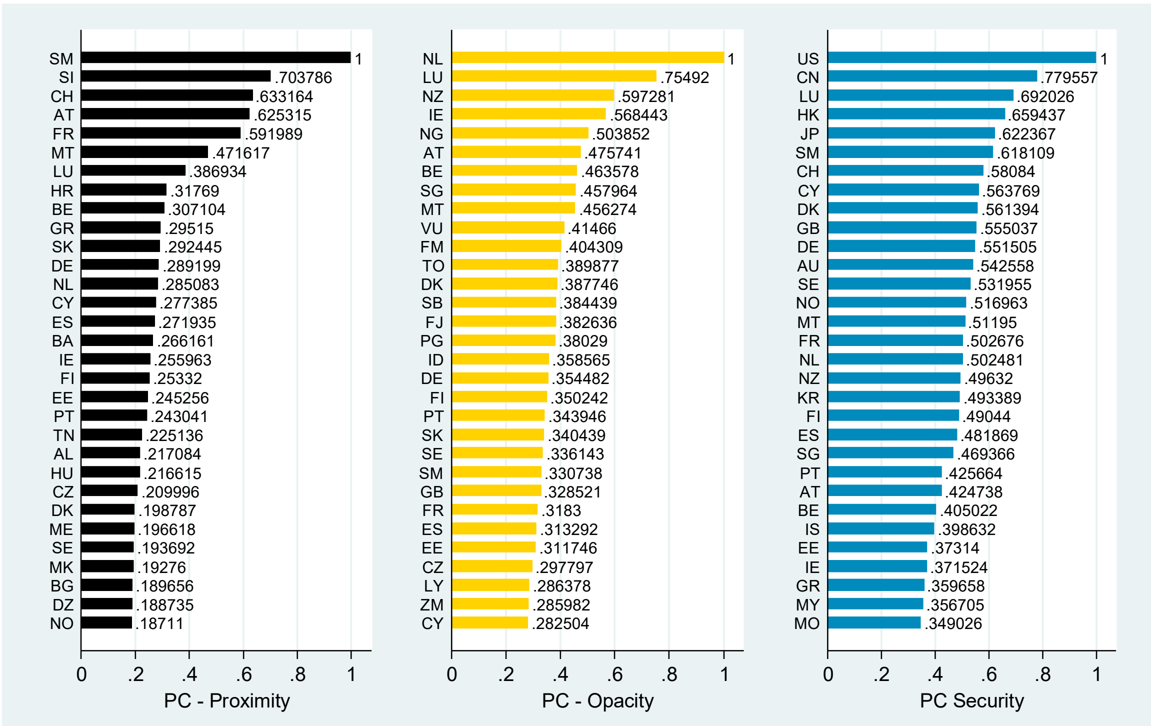
Notes: Loadings with the 3 identified principal components are displayed. Loadings <|.2| are not shown in the table. Components rotation: Varimax.

Source: Author's elaboration of various sources

The three retained components are relatively easy to interpret. The first component can be interpreted as measuring the *proximity* risk dimension. The second component is primarily dominated by the variables that indicate economic size (*GDP*), financial size (*bank_credit*) and regulatory stability (*rule_law*). It can thus be interpreted as measuring the *security* dimension. The third component shows strong positive coefficients with corporate *complexity* and *unavailability* and a positive (but not strong) loading with *comm_currency* and *cash_supply*. Therefore, it can be interpreted as measuring *opacity*, albeit with some preference to the Euro zone (being i=Italy).

The scores for each case (i.e. country) are therefore computed and normalised (min-max on a 0-1 scale) to allow for comparison. Figure 2 below reports the first 30 countries in terms of their value for each of the three retained PCs, i.e. the three ML risk dimensions.[12]

Figure 2 – Top 30 countries for the three principal components: *Proximity, Opacity, Security*



Source: Author's elaboration of various sources

4.1.1 Proximity

San Marino (SM), Slovenia (SI), Switzerland (CH), Austria (AT), France (FR) and Malta (MT) show the highest scores with respect to the principal component identifiable in the *proximity* ML risk dimension. The first five countries share a border with Italy (SI, AT, FR are also part of the EU and the Schengen area), while Malta is reachable from Sicily in 2 hours via ferry boat. The Italian borders with Switzerland and Slovenia are those witnessing the greatest seizures of undeclared cash, bank cheques and other credit notes (Guardia di Finanza, 2019).[13] San Marino, Malta and Switzerland are also the countries with the highest percentage of Italian speakers. In particular, Italian is the official language in SM, while it is one of the four official languages in Switzerland – and the most spoken in the Canton of Ticino (the Swiss canton with the highest evidence of ML related to Italian individuals - Fedpol, 2014, 2019,).

[12] It is important to reiterate that the three identified components do not show the values of Italy, because the country pair *ij* where *i*=*j*=Italy was dropped from the dataset.

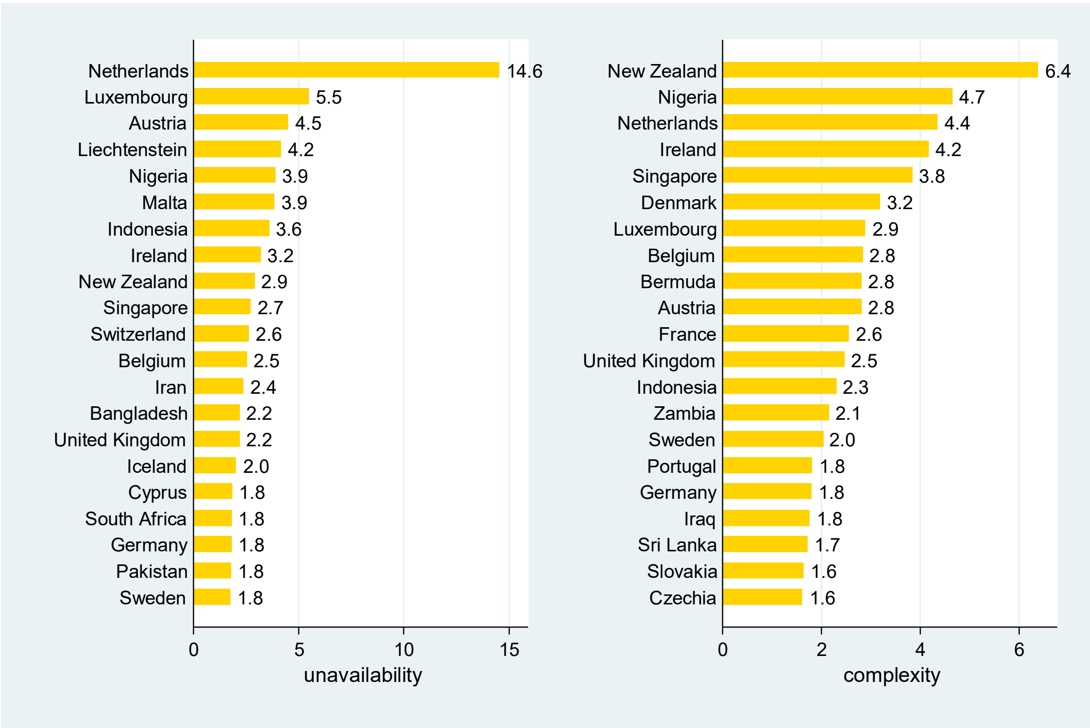
[13] in December 2019, Italian-Swiss border guards seized a single bank cheque worth 100 million euro (issued by the Credit Suisse bank of Geneve) from two individuals with previous for drug trafficking (Campaniello, 2019).

4.1.2 Opacity

The Netherlands (NL), Luxembourg (LU), New Zealand (NZ), Ireland (IE), Nigeria (NG), Austria (AT), Belgium (BE), Singapore (SG), Malta (MT), and Vanuatu (VU) are the ten j-countries with the highest score with respect to the principal component labelled as *opacity* ML vulnerability (Figure 20). In particular, countries like Luxembourg rank high for all the sub-dimensions of proximity: in terms of payment anonymity, Luxembourg has the highest cash supply value (value of M1 stock that is 440% of its GDP in 2017[14]), has no limits on cash purchases and is the main issuer of 500 and 250 euro banknotes, which are among the most frequently used in bulk cash smuggling according to a wide literature (Europol, 2015; Soudijn & Reuter, 2016; Riccardi & Levi, 2018). Luxembourg rank high also in terms of corporate opacity, especially in terms of unavailability of corporate information

But under this dimension, is the Netherlands standing promptly: for around 15% of Dutch companies, it is not possible, due to opaque corporate vehicles that act as holding entities, to identify the natural person behind 50% of their ownership structures. This share is more than 10 times higher than the global mean (1.15%). This may be due primarily to the wide use of Dutch foundations (*stichting*): these legal arrangements are used extensively in the country for legitimate purposes, but their ML vulnerabilities have been also frequently highlighted by both international organisations and NGOs (see e.g. OECD, 2019, pp. 25–27).

Figure 3 – Business ownership *unavailability* and *complexity*: percentage of firms in the highest risk class. Top 20 countries



In terms of business ownership complexity, the Netherlands rank high, together with countries such as the New Zealand, Nigeria, Ireland, Singapore, Luxembourg, Denmark (more than 3% of their firms fall in the highest BOC class). In New Zealand, the average distance between a firm and its beneficial owners is more than 4 (i.e. there are 3 intermediate owners between the firm and its ultimate owners). Dutch, Irish, Angolan, South African, Bermuda and Luxembourg firms have similar values.

[14] As a matter of comparison, the second in the ranking is Libya with a M1/GDP ratio of 200%, and the third is Japan with 130%. Italy, Germany, Sweden, France have a cash supply value which is about 60% of their GDP (World Bank, 2017).

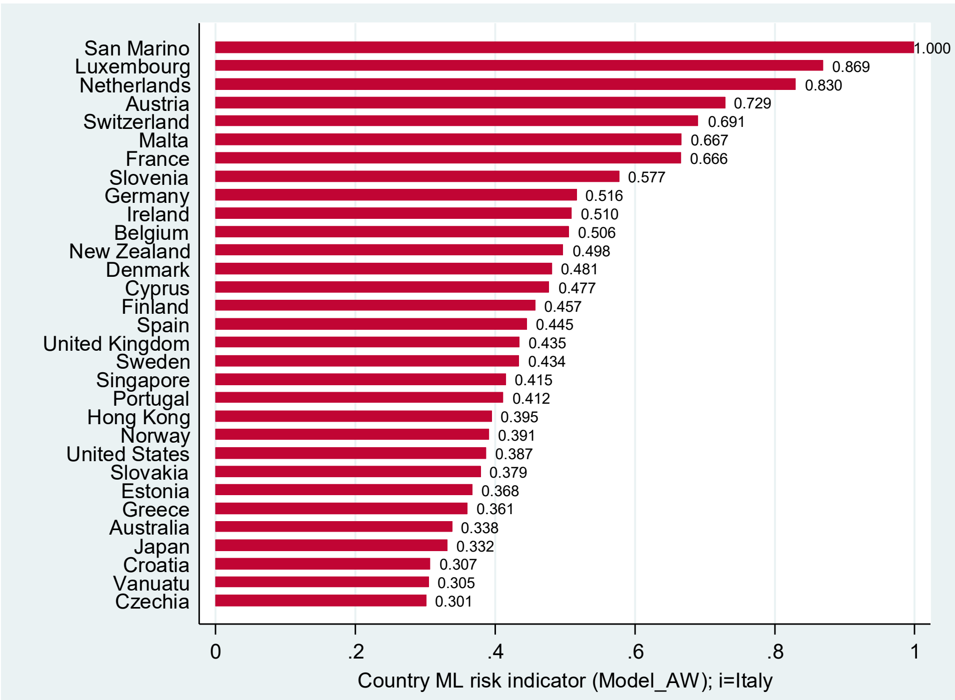
4.1.3 Security

In terms of security, highest values are associated to large and strong economies, with the countries having the greatest GDP on top (US, China, Japan). Among the three variables associated with this principal component, the only one worth to be discussed is the bank credit ratio (i.e. the value of the overall bank credit to the private sector as % GDP), which may be read as the degree of banking specialisation of the economy. The highest values are those of Hong Kong (223%), Cyprus (194.3%), Switzerland (174.6%), San Marino (172.9%), Denmark (163.1%) and China (157%). Countries ranking on top of the World Bank's rule of law are Nordic countries (Finland, Norway, Sweden), Swizerland, New Zealand, Denmark and the Netherlands.

4.2 Aggregation and construction of the ML risk composite indicator

The next step is to construct the composite indicator of ML risk by aggregating the scores extracted from the three identified principal components for each case (i.e. country). The indicator is a weighted average of the 3 PC scores that uses as weights the proportion of variance (of the model) explained by each component (as in Riccardi, Milani & Camerini, 2018 and as suggested by OECD, 2008). Results are reported in the figure here below. The top *j*-countries in terms of ML risk from the perspective of the *i*-country Italy, as resulting from this aggregation, are San Marino, Luxembourg, Netherlands, Austria, Switzerland and Malta.

Figure 4 –ML high-risk countries from the perspective of Italy. Top 30 high-risk countries



Note: the following countries (which could be relevant in terms of ML vulnerability from the Italian perspective) were not included in the dataset because of missing values for some of the variables employed in the PCA: Marshall Islands, American Samoa, BVI, US Virgin Islands, Andorra, Isle of Man, Jersey, Monaco, Curacao, Holy See and Liechtenstein

Source: Author's elaboration of various sources

Technical validation: sensitivity analysis

Before providing an empirical validation to this result, the indicator is also *technically* validated through sensitivity analysis and robustness check. In particular, I test whether the results significantly change depending on changes in the parameters used in the PCA (e.g. related to rotation, normalisation, aggregation, weighting and variables selections). 20 further PCA models are calculated, each of which produced a further version of the indicator (see Appendix). The correlation among the 21 obtained indicators (including the one above presented) is always higher than .95 (and always significant), confirming that the result above reported is robust and irrelevant to changes to methodological choices.

4.3 Empirical validation

To validate empirically the new ML risk indicator, the ranking of 'high-risk countries' as stemming from the analysis (having *i*=Italy) is compared to observed evidence of ML, and in particular to the list of foreign jurisdictions employed by Italian individuals arrested or sentenced for ML activities (and flagged in the Lexis Nexis WoCo database). Results are discussed here below.

4.3.1 Foreign ML activity of Italian individuals: evidence from the WoCo dataset

Table 5 reports the data on Italian individuals involved in ML and included in the WoCo dataset. A total number of 2818 Italians were identified. Those who laundered only in Italy corresponded to 36.5% of the total number. Those laundering both in Italy and abroad to 59.3%, while only 2.6% laundered in foreign countries. In total, 75 countries are mentioned as observing at least 1 episode of ML by Italian individuals (76 including Italy). Overall, foreign countries were mentioned about 1,700 times in WoCo records.

Table 5 – Italian individuals involved in money laundering: descriptive statistics

	Number	% on relevant total
A. Individuals in the dataset (total)	**2818**	**100%**
Individuals laundering only in Italy	1029	36.5%
Individuals laundering both in Italy and abroad	1667	59.3%
Individuals laundering only abroad	73	2.6%
Individuals with no info available on ML location	45	1.6%
B. Countries mentioned in the dataset (as location of ML activity)	**3092**	**100%**
Mentions of Italy	1399	45.2%
Mentions of foreign countries	1693	54.8%
N. foreign countries mentioned	75	

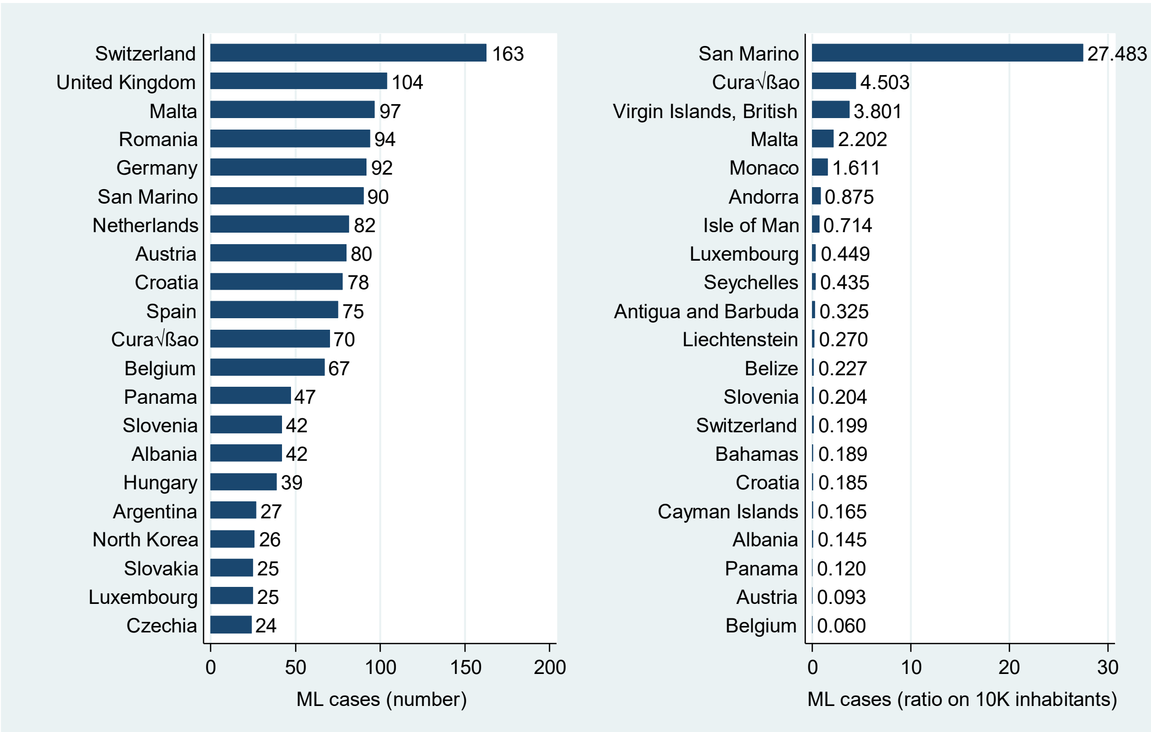
Source: Author's elaboration of Lexis Nexis WorldCompliance

These statistics themselves could be a further confirmation of the validity and relevance of the *proximity* hypothesis: when laundering, Italians prefer staying at home. And this hypothesis is further confirmed looking at the most frequently mentioned foreign jurisdictions (Figure 5): the first ten in terms of cases are European countries (7 are part of the EU) and three of them are countries bordering with Italy (while Malta, Germany, Croatia are only few hours driving distant).

This finding may be influenced by the type of ML *threat* – i.e. the type of offence and/or criminal involved. For example, as discussed in Section 2, it could be hypothesised that Italian mafias could more likely launder domestically or in closer countries (in geographic, cultural and social terms) because of the need to benefit from the control of the territory. In this case it was difficult to precisely identify the predicate offences behind the ML cases, but out of the 12,467 offences mentioned by WoCo reports together with the ML activity, about 20% corresponded to an organised crime accusation, in most cases a mafia-type one. Looking at other sentinel crimes of mafia activity, in 11% extortion was mentioned. This means that for at least 30% of the reported ML offences a link with organised crime, especially mafia-related, could be observed. In terms of persons, almost half of the dataset represents individuals with mafia links. Among the rest, prevailing associate/predicate offences are fraud (10% of the total), tax crime (6%) and drug trafficking (6%).

For sure, the jurisdictions standing on top of the list emerging from WoCo have wide evidence of money laundering related to Italian mafias. Switzerland has been heavily used for laundering money by Cosa Nostra clans (e.g. in the well-known *Pizza Connection* operation), the 'Ndrangheta (e.g. *Decollo, Galassia, Crimine 2, Rinascita-Scott, Game Over* investigations) and Camorra groups (e.g. *Megaride, Spartacus, Cartagena*). The risk posed by Italian mafias in terms of money laundering has also been extensively acknowledged by the Swiss authorities themselves (Fedpol, 2014; 2019). There is also wide evidence of ML of Italians in the UK (Campana, 2011; Allum, 2014; Calderoni et al., 2015; Transcrime, 2018), both in firms and in the real estate sector. Malta has recently become the new frontier of ML by Italians, especially in relation to gambling and gaming companies (more than 10 police investigations involving Italian mafias and Maltese gaming companies have occurred in the last 5 years, e.g. operations *Gambling, Jonny, Jamm Jamm, Jackpot, Imitation game, Master Bet, Game Over* - Transcrime, 2018 for a review). San Marino, despite some recent improvements pushed by the Italian AML authorities, has been and is still hosting bank accounts and firms related to Italian criminal organisations (e.g. *Black Hawk, Tibet, Pollicino, Titano, Malavigna* investigations), also involved in recent Covid-19-related fraud. Germany, the Netherlands, Romania, Spain are frequent countries of transplantation of Italian mafias with occasional episodes of ML and infiltration of the legitimate economy, too (KLPD - DNR, 2011; Ferwerda & Unger, 2016; Calderoni et al., 2015). Operations *Pollino, Meltemi, Styx, Acero-Krupy* confirm this phenomenon.

Figure 5 – Foreign countries involved in ML activities by Italian individuals: number of cases and ratio of the population. Top 20 countries



Note: a 'case' is an individual-country pair. An individual could be associated with more than one country. Total number of country pairs: 3092 (1693 excluding Italy)

Source: Author's elaboration of Lexis Nexis WorldCompliance data

4.3.2 Correlation between the risk indicator and the measure of ML evidence

The new risk indicator (with i=Italy) is therefore compared with the list of countries involved in ML cases, both taken in terms of count and as ratio to the population. The correlation between the indicator

(*ML_index*) and the ML cases (see Table 7) is high and significant (.61). Also the three principal components – i.e. the proxies for *proximity, security* and *opacity* – are positively correlated, when taken individually, with the first (proximity) showing the highest degree of association.

Table 6 – Observed ML cases v. ML risk indicator: Pearson's correlation

	ML_cases_{ij}	$ML\_cases\_pop_{ij}$	$\boldsymbol{ML\_index_{ij}}$	$PC1\_proximity_{ij}$	$PC2\_security_{ij}$	$PC3\_opacity_{ij}$
ML_cases_{ij}	1					
$ML\_cases\_pop_{ij}$	0.308***	1				
$\boldsymbol{ML\_index_{ij}}$	**0.613*** **	**0.384*** **	1			
$PC1\_proximity_{ij}$	0.653***	0.575***	0.788***	1		
$PC2\_security_{ij}$	0.404***	0.193**	0.809***	0.421***	1	
$PC3\_opacity_{ij}$	0.331***	0.087	0.668***	0.372***	0.298***	1

*Notes: i=Italy. *, **, and ***, indicate coefficients significantly different from zero at the 95.0%, 99.0%, and 99.9% confidence level, respectively.*

The relationship between the ML risk indicator and the actual volume y_{ij} of ML cases in country j originating from *i* is further tested in the following regression model, with *i*= Italy:

$$y_{ij} = ML\_cases_{ij} = \beta_0 + \beta_1[ML\_index_{ij}] + \beta_2 W_j + \varepsilon_{ij}$$

Where y_{ij} is the number of ML cases as measured and presented above; W_j is a set of control variables that refers to country *j*. Specifically, I control for both the population in country *j* and for the number of cases in which country *j* was involved in the commission of other offences (as aforesaid, *predicate* or *associate* offences) related to the same set of individuals involved in ML. This was conducted to test whether the relation between the observed measure of ML and the level of ML risk as estimated by my indicator remained significant even after controlling for both the size of country *j* and for the volume of criminal activities associated with the ML cases. The latter could be interpreted as a means through which to test whether the risk of country *j*, as a function of its *ML vulnerabilities*, is invariant to the level of *ML threats* therein conducted.

Table 7 below reports the coefficients of the explanatory variables of eight negative binomial regression models. Negative binomial (Neg.bin.) regression is used because of the count and overdispersed nature of the dependent variable. The standard form is preferred to a zero-inflated negative binomial (ZINB) because, despite the high number of zeroes of the dependent variable, the Vuong test did not indicate a strong preference for ZINB than for Neg.bin. Moreover, I did not have strong hypotheses about the variables for the binary part of the model, i.e. the one explaining the excess zeroes. However, one model (Model 8) using ZINB is also estimated and is displayed below. [15]

Table 7 – Observed ML cases v. ML risk indicator: Regression models

Dependent variable = y_{ij}= ML_cases_{ij} where *i*=Italy

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ML_index_j	5.82***	5.82***	4.75***	-	-	-	-	-
PC – proximity	-	-	-	11.58***	-	-	9.40****	-
PC – opacity	-	-	-	-	5.67***	-	-0.81	2.10^a
PC - security	-	-	-	-	-	6.79***	3.05**	3.21**
$population_j$	-	1.17e-10	-1.05e-10	5.12e-09	1.32e-09	-2.7e-09***	6.39e-10	-

[15] Other methods and model specifications were tested. Namely, OLS models and Poisson models did not produce different results than those reported in the table. Also semi-log models were employed, by log-transforming the explanatory variables relative to the ML index and its principal components (in this way, adopting the typical 'gravity model' functional form – see Cassetta et al., 2014; Ferwerda et al., 2012; Aziani et al., 2020). The findings did not change in a sensitive manner. ZIP tests also highlighted preference for Neg.bin than to Poisson and zero-inflated Poisson models.

other_crimes$_j$	-	-	0.064***	-	-	-	-	-
constant	0.43	0.43	0.20	-0.47	0.66	0.16	-0.57	1.23**
Logit part								
PC – proximity	-	-	-	-	-	-	-	-14.3***
constant	-	-	-	-	-	-	-	2.03***
Method	Neg.bin.	Neg.bin.	Neg.bin.	Neg.bin	Neg.bin.	Neg.bin.	Neg.bin.	ZINB
N. obs.	164	164	164	164	164	164	164	164
Wald chi2	35.57	35.63	57.83	17.58	10.8	33.5	24.02	19.95
Prob > chi2	0.0000	0.0000	0.0000	0.0002	0.005	0.0000	0.0001	0.0000
AIC	670.97	672.97	663.45	671.93	692.15	678.42	672.14	667.35
BIC	680.27	685.37	678.95	684.33	704.55	690.82	690.73	685.94
Pseudo R^2	0.039	0.039	0.055	0.040	0.011	0.031	0.046	-

Notes: Model 1-7: Negative binomial regressions. Model 8: Zero-inflated negative binomial (ZINB). In Model 8: PC Proximity *was employed in the binary part of the model (a logit), while* PC Opacity *and* PC Security *were employed in the Neg.bin. part. Displayed coefficients in Model 8 refer to the respective parts of the model. Robust standard errors are calculated in all models. The Akaike's (AIC) and the Bayesian information criteria (BIC) provide two measures of the relative quality of the models. Markers [a], *, **, and ***, indicate coefficients significantly different from zero at the 85%, 90%, 95%, and 99% confidence level, respectively.*

In models 1, 2 and 3 the coefficient of *ML index* is always positive and significant, also after controlling for the population (Model 2) and the level of other (non-ML) criminal activities (Model 3). Moreover, the positive and significant coefficient of the variable *other_crimes* suggests that the actual number of ML cases is higher, the higher the number of *associate/predicate* offences conducted in the same country where ML takes places. This can be interpreted as a further confirmation of the proximity hypothesis, in the sense that ML will be more likely not only if the location is closer to where criminal actors are active/come from, but, as in this case, also where predicate crimes are committed.

Models 4 to 8 instead use as explanatory variables the three principal components which are constituting the indicator, namely *proximity, opacity* and *security*. When taken individually, the coefficients of the three components are always positive and significant, also after controlling for the population of the destination country (country *j*). When taken together (Model 7), proximity and security keep their explanatory value, while opacity loses its significance, suggesting that this driver may be less important than the other two components in explaining the global distribution of ML cases related to Italian individuals or, alternatively, that its effect may be captured by the two other variables, and in particular by *proximity,* since a high number of the jurisdictions ranking highest in terms of this principal component (see above) are also close to Italy in geographic, linguistic and monetary terms.

Finally, Model 8 adopts a ZINB to test the hypothesis that the laundering of dirty money originated from Italian individuals could be modelled in two processes: (1) one (the logit part of the ZINB) explaining whether a country attracted any ML activity; (2) the second (the Neg.bin. part) explaining the volume of ML activities, i.e. the count of cases. Specifically, it is hypothesised that *proximity* determines if a country receives dirty funds or not; while *opacity* and *security* determines the volume of dirty funds received, i.e. the volume of ML cases hosted by the country. The idea is that a criminal would decide to launder abroad only if at a reasonable (geographic, cultural…) distance; then he would choose those jurisdictions, holding proximity constant, which are most reliable and most capable to conceal his funds. Results suggest that the closer the j-country to Italy (from a geographical, cultural and monetary perspective), the more likely that it attracts ML cases involving Italian individuals (see the negative and significant coefficient of *proximity* in the logit part); the number of ML cases instead increases with an increase in the level of *security* of the country, while, again, *opacity* is only weakly significant.

5. Discussion and Conclusion

The regressions confirm the fit of the model to the Italian case, and in particular that the ML risk indicator, applied to Italy, is highly correlated with the observed evidence of ML and is able to explain the distribution of ML cases of Italian individuals outside the country. This result confirms that risk, conceived as a function of ML vulnerabilities, is expedient for explaining how ML activities are actually distributed across foreign jurisdictions, also when controlling for (proxies of) ML threats. The empirical validation also confirms the goodness of the idea of ML risk as a *relational* phenomenon, that is, that destination countries (countries *j*) have different levels of ML risk depending on the country the illicit money originated from (country *i*). One must keep in mind that the application of the methodology (and its empirical validation) was conducted in a single country, but some broader considerations can be made.

5.1 The importance of proximity

The significance of the proximity dimension confirms the validity of gravity models for explaining illicit financial flows. In particular, the works of Walker and Unger, which have been further developed by other scholars (e.g. Ferwerda et al., 2012; Cassetta et al., 2014; Ferwerda et al., 2019; Gullo and Montalbano, 2019; Aziani et al. 2020), to apply gravity approaches to model ML is fully supported by this paper. The findings also support previous empirical studies showing that proximity is an important driver of crime and ML (Gara & De Franceschis, 2015; Kruisbergen et al., 2015; Steinko, 2012; Petrunov, 2011). If *small is beautiful* for illegal enterprises (Reuter, 1983), *close is beautiful* for money laundering. One could question whether this result – the importance of proximity – characterises only the laundering of 'Italian' dirty money, as it could be due to two causes: (i) the heavy presence of individuals linked to Italian mafias in the dataset (about 59%), who could more likely launder close to their country of; and, as just mentioned, (ii) the proximity of Italy to countries with high levels of opacity (as here operationalised).

5.2 Secrecy beyond the Caribbean

The popular perception is that *secrecy countries* are often small, exotic, and offshore, located somewhere in the Caribbean or the Pacific sea. They pop up regularly in high-profile media leaks like the Panama Papers or Paradise Papers. The (novel) measures of corporate opacity used in this thesis, and employed for the construction of the indicator, demonstrate instead that certain European (and even EU) countries have a level of secrecy that is equal, or even greater, than Caribbean countries and other offshore jurisdictions. In particular, European countries have the highest volume of firms with anomalous complexity of their corporate structure and with the lowest information on their beneficial owners. Most notably, the Netherlands, Luxembourg, Malta, Ireland, Liechtenstein, Austria and, to a lesser extent, the UK are the highest ranked at the global level. While these countries performed badly with respect to actual corporate opacity, they perform well in terms of *statutory* measures of transparency (hence, why they have pretty good scores in, e.g., the FATF ratings or the FSI's Secrecy Score). The gap between *actual* opacity and lack of compliance with transparency requirements is something which current official AML blacklists are not able to bridge.

5.3 Even ML offenders want to stay safe

Also security – i.e. the strength of the economic, financial and institutional structure of the destination country – appears as a key driver of ML flows, at least those related to Italian individuals. The security component is positive and significant in all regression models. It is possible to compare the ML risk indicator, and the ML cases, with a set of contextual variables (Table 9 and 10).

Table 8 – Average values of contextual variables, by risk classes of the ML indicator

ML_index risk class	Pop. (M)	GDP per capita	GDP growth	Inflation rate	Statutory corp tax rate	Effective corp tax rate	Pretax profit ratio	Control of corrupt.
Very high risk	14.6	56893.6	2.8%	0.8%	26.1%	14.0%	1.5	0.83
High risk	36.2	42295.5	2.8%	0.9%	23.5%	18.3%	0.7	0.81
Medium risk	59.4	17169.4	2.7%	1.9%	22.0%	11.3%	3.8	0.53
Low risk	47.6	9148.2	3.4%	4.0%	23.1%	5.6%	5.0	0.44
Very low risk	34.0	3538.2	3.3%	8.7%	26.1%	18.6%	1.1	0.23
Mean	**42.4**	**15065.4**	**3.1%**	**4.6%**	**24.1%**	**13.4%**	**2.5**	**0.45**

Notes: Five risk classes of the ML indicator identified through k-means clustering based on Euclidean Distance. (a) Population: mean 2014-18 (million inhabitants); (b) GDP per capita: US dollars current prices, 2017; (c) GDP growth: annual growth, mean 2014-18; (d) Inflation rate: mean 2014-18; (e) Statutory corporate tax rate provided by KPMG; (f) Effective corporate tax rate as estimated by Torslov et al., 2020; (g) Pretax profit on employees compensation ratio, as estimated by Torslov et al., 2020; (h) Control of Corruption, normalised on a 0-1 scale. Source for (a), (b), (c), (d), (h) is World Bank.

Source: Author's elaboration of various sources

Table 9 – Correlation between the risk indicator and contextual variables

	ML_index	ML_cases
ML_index	1	
ML_cases	0.613***	1
Population	0.0005	-0.0039
GDP_per capita	0.746***	0.252**
GDP_growth	-0.064	-0.0608
Inflation rate	-0.218**	-0.0443
Statutory corp tax rate	-0.081	-0.0086
Effective corp tax rate	0.256*	0.1356
Control of Corruption	0.775***	0.273**

*Notes: *, **, and ***, indicate coefficients significantly different from zero at the 90%, 95%, and 99% confidence level, respectively.*

Source: Author's elaboration of various sources

Results tend to point out to the same direction: ML cases related to Italian individuals are found to be more prevalent in countries with stronger economy (in terms of both GDP), richer (higher GDP per capita), a more prominent financial sector (measured as bank credit as % of GDP), a stronger rule of law and better control of corruption. Moreover, the ML risk indicator is also negatively correlated with inflation rate. That is to say, high-risk ML countries (at least from the perspective of Italy) are usually wealthier, less corrupt, and stable jurisdictions. The findings provide support for the hypothesis, discussed in Section 2, that, when it comes to ML, criminals prefer, ceteris paribus, reliable destination countries. Again, the findings of these papers seem to confirm the suggestions of the 'illegal enterprise theory' (Reuter, 1983; Malm and Bichler, 2013).

5.4 Corruption, taxation and money laundering

The risk indicator is also positively correlated with control of corruption, as is the amount of observed ML cases. Those countries that are better equipped to control corruption (according to the World Bank), are more vulnerable to ML, at least to the ML activities conducted by Italian criminals. This finding, which appears to contradict common-sense, confirms the hypothesis of corruption as a *cost* for money laundering, or at least a source of insecurity for ML offenders. Given that these criminals want to better safeguard their funds, they may avoid, ceteris paribus, countries with high corruption levels.

The analysis found a null correlation between the risk of ML (from the Italian perspective) and the level of statutory corporate tax rates, and a weak positive correlation with effective corporate tax rates (as estimated by Tørsløv et al., 2020). The distribution of ML cases outside of Italy were shown to not be significantly correlated with tax levels. Therefore, the findings do not confirm the hypothesis that illicit proceeds are attracted to favourable tax jurisdictions, supporting previous studies (Gullo and Montalbano, 2018; Aziani et al, 2020; Ferwerda et al., 2019). As discussed, the belief that tax havens are also good destinations for ML, although quite popular in the media debate, does not build on solid empirical evidence.

5.5 The new ML risk indicator vs. official AML blacklists

But, from a policy perspective, one of the most interesting findings is about the relation between the newly created ML risk indicator and the official AML/CTF blacklists. Are they correlated? And which one, between the two lists of 'high-risk countries', is most capable to explain the observed evidence of ML carried out by Italian individuals?

Table 11 answers this question. Following Littrell and O'Brien (2019), it shows the correlation of the new indicator (*ML_index*) and of the actual ML cases (*ML_cases*) with (i) the FATF blacklist in the period 2000-2006; (ii) the FATF blacklist and greylist in the period 2000-2006 and 2008-2020; (iii) the FATF scores of Technical Compliance and Effectiveness; (iv) the US INCSR list of 'major money laundering countries' in the 2008-2020 period; (v) the Tax Justice Network Financial Secrecy Index and Secrecy Score (in the 2020 version); (vi) the Basel AML index; (viii) the Walker's attractiveness index (2009) and (ix) the list of high-risk countries as stemming from recent media investigations such as Panama Papers, Paradise Papers and Russian Laundromat. As for how all these measures are operationalised and measures, see Appendix.

Some elements are evident. First, the newly created indicator is the one showing the highest correlation with observed evidence of ML, almost double the value than all other measures of ML risk. Second, the new indicator shows positive correlation with Tax Justice Network's FSI, with Walker's index and, to a lesser extent, with media investigations such as Panama Papers and Russian Laundromat. Third, and most important, the new indicator has a negative (and significant) correlation with most AML official blacklists. Blacklists show also negative (or null) correlation with the observed evidence of ML activity of Italian individuals.

Table 10 - Correlation between ML risk indicator, ML cases, blacklists and other risk measures

	ML_index	ML_cases	ML_cases_pop	FATF_BL_2000_2006	FATF_BL_2008_2020	FATF_GL_2008_2020	FATF_Tech_compliance	FATF_Effectiveness	INCSR_2008_2020	SS_2020	FSI_2020	Basel_AML_2019	Walker_2009	PanamaPapers_2016	ParadisePapers2017	RussianLaundromat_2017
ML_index																
ML_cases	0.61															
ML_cases_pop	0.38	0.31														
FATF_BL_2000_2006	-0.09	-0.07	-0.03													
FATF_BL_2008_2020	-0.12	-0.04	-0.03	0.09												
FATF_GL_2008_2020	-0.30	-0.10	-0.06	0.03	0.30											
FATF_Tech_compliance	-0.30	-0.19	-0.07	0.01	0.16	0.09										
FATF_Effectiveness	-0.43	-0.32	-0.01	-0.05	0.21	0.43	0.55									
INCSR_2008_2020	0.04	0.19	-0.03	0.22	0.16	0.14	-0.06	-0.26								
SS_2020	-0.39	-0.21	0.00	0.08	0.00	0.19	0.17	0.45	-0.02							
FSI_2020	0.39	0.27	-0.06	-0.09	-0.05	-0.11	-0.05	-0.27	0.37	0.14						
Basel_AML_2019	-0.54	-0.25	-0.15	0.08	0.34	0.54	0.52	0.67	0.27	0.56	0.06					
Walker_2009	0.51	0.30	0.12	0.09	-0.01	-0.11	-0.19	-0.38	0.72	-0.09	0.74	-0.16				
PanamaPapers_2016	0.19	0.21	0.09	0.00	-0.05	-0.04	-0.10	-0.18	0.28	0.11	0.39	-0.01	0.37			
ParadisePapers2017	0.04	-0.01	-0.01	0.07	-0.04	-0.05	0.04	0.02	0.08	0.18	0.10	-0.06	0.09	0.06		
RussianLaundromat_2017	0.24	0.33	0.00	-0.03	-0.05	-0.08	-0.13	-0.31	0.30	-0.13	0.33	-0.10	0.33	0.45	0.05	

Notes: Pearson's r. Blue color highlight positive correlation; Red negative correlation. Lighter colours mean lower or no statistical significance. Correlation matrix with indications on statistical significance is reported in the Appendix

Source: Author's elaboration of various sources

To further dig this result, the table below reports the number of countries appearing in the current (and latest, as of May 2020) FATF, US INCSR and EU blacklists and grey lists by risk class of the ML indicator developed by this paper.[16] No countries classified as being at 'very high' risk or 'high-risk' by the indicator are included in the FATF and EU blacklists and grey lists. Only one country in the 'very high' risk class of my indicator (the Netherlands) was classified as a *"major money laundering country"* by the US INCSR, while five were categorised in the 'High' cluster. In summary, being in a FATF or EU black or grey list is a good proxy for being at a low-risk of ML according to the methodology developed here (at least in its implementation to the Italian context).

Table 11 – ML risk class v. FATF, EU and US INCSR blacklists and grey lists

ML_index risk class	N. countries	FATF blacklist *Feb 2020*	FATF grey list *Feb 2020*	US INCSR "Major ML countries" *2020*	EU "high risk third countries" list *May 2020*
Very high risk	7	0	0	1	0
High risk	21	0	0	5	0
Medium risk	31	1	3	11	3
Low risk	50	0	5	26	6
Very low risk	66	0	5	27	7
Total	**164**	**1**	**13**	**70**	**16**

Notes: Five risk classes of the ML indicator identified through k-means clustering based on Euclidean Distance. The number of countries in blacklists and grey lists displayed in the table could be lower than the actual one because of missing values in the ML risk indicator.

Source: Author's elaboration of various sources

This finding is puzzling. The countries which are at the highest risk in fact are instead positive benchmarks for the FATF? How can we explain it? First, it must be stressed that the risk indicator and the observed evidence pertained solely to the ML of Italian individuals. As such, it may well be possible that, when validated in other countries, the indicator will be differently correlated with blacklists, as it will with ML cases. Second, it may also be possible that criminals explicitly avoid blacklisted or grey listed jurisdictions so as to not set-off alarms amongst AML obliged entities and regulators, and avoid heavier monitoring. One of the (unintended) consequences of blacklisting could be a displacement effect, which is to say criminals may seek to avoid blacklisted countries and opt for those jurisdictions that are currently above any suspicion. For Italian criminals, this means, first and foremost, EU member states.

A third explanation pertains to the intrinsic nature of official blacklists. What precisely do they measure? As mentioned in the introduction, they have been widely criticised because of the weak, obscure and politically-driven evaluation methodologies (Ferwerda & Reuter, 2020; Halliday et al., 2019; Littrell & O'Brien, 2019; Levi et al., 2018; Riccardi, 2020; Tax Justice Network, 2018; van Duyne & van Koningsveld, 2017). For sure, despite the recent introduction by FATF and the EU of an *Effectiveness* criteria, blacklists tend to assess countries' technical compliance to AML regulations and recommendations, but are not aimed to measure actual ML risk.

5.6 Policy implications

The empirical validation confirmed the goodness of the idea of ML risk as a *relational* phenomenon, that is, that destination countries (countries *j*) have different levels of ML risk depending on the country the illicit money originated from (country *i*). This poses an important policy implication: a single, unique and universally valid list of 'high-risk countries' is simply not appropriate for describing a relational

[16] The indicator was clustered into five risk classes through a k-means clustering technique based on Euclidean distance.

phenomenon such as ML. Obviously, to fully demonstrate this hypothesis, further empirical validations across more origin countries should be conducted, so as to not limit such considerations solely to when i=Italy. However, if this will hold, it means that - if one were being provocative - bilateral (or regional) meetings could be more effective for addressing country-specific risks than large worldwide plenaries in the FATF-style. This should not be interpreted necessarily as constituting a step back in the evolution of the global fight against ML. Rather, having relational risk ratings could actually help to better orient the investigation and intelligence activities of law enforcement, FIUs and tax agencies, and making international cooperation more effective.

Generally speaking, the analysis here conducted proposes a more objective and empirically validated measure of ML risk which could aid the revision of the AML blacklisting process by the FATF, EU and US. Supporting official assessments with stronger empirical evidence could help to improve their acceptance from the perspective of the international community, avoid critiques and also reduce the harm of (unjustified) de-risking phenomena.

Also, it could support the efforts on UNODC in developing a new methodology to *measure illicit financial flows*, as part of the global debate on United Nations Sustainable Development Goal 16.4 (UNODC, 2017).

5.7 Limitations and further research directions

The analysis nevertheless suffers from many limitations, which should be addressed in future research. First, the methodology developed in this paper was tested in one country only, Italy. Hence, it would be necessary to apply the model in further i-countries, with the express purpose of producing further indicators which can then be validated against a wider set of observed measures of ML (which I was not able to do in this research).

Second, the model employed here was intentionally simplistic: ML risk as a function of vulnerabilities only. The role and influence of *threats* – i.e. of criminal actors and predicate offences – in determining where and how illicit proceeds move across countries should be better understood and modelled in follow-up studies. Moreover, the different role of countries in the global ML supply and demand should be taken into account. Some act as final destinations of illicit money, other as "*throughflow jurisdictions"* (Ferwerda et al., 2019). Future research should aim at *disaggregating* between different types of flows, predicate crimes and types of destination countries (Reuter, 2017).

The Lexis Nexis WoCo dataset was used for the first time by this paper in academic research. Although for the purposes of this thesis only some of the information collected was used, I believe that such data could be highly informative and open up new avenues of empirical research in crime studies, especially when microdata on offenders are not available. However, the quality and representativeness of this dataset should be closely audited.

The ML risk measure developed by this paper heavily relies on the inputs provided by the criminological literature. The promising results of this work suggest to keep on pursuing this avenue. This may mean bringing money laundering 'back home': stealing it back from economists – who monopolised this research area for years – and putting crime studies at the centre of the scene. Criminological research can still say very much about why, how – and where – ML offenders operate, and therefore how ML risk will distribute and evolve.

APPENDIX

a. Collection and processing of ML evidence from the WoCo dataset

The following is an example of how the information included in Lexis Nexis WorldCompliance dataset was collected and processed in order to extract the data on the (foreign) countries involved in money laundering schemes by the Italian individuals in the sample. Table A1 reports the information included in the original dataset Lexis Nexis World Compliance (LN WoCo) with respect to one of the 2818 individuals, and Table A2 some of the information included in the news linked in the LN WoCo dataset. Table A3 how the information is then processed and classified and results as counts for the categories related to the types of associate/predicate offences, to the mentions of countries as locations of ML activity (ML_cases_j) and as locations of associate/predicate offences ($other\_crimes_j$). In the case under examination, for example, the field 'Remarks' of the Lexis Nexis dataset mentions only San Marino; the analysis of the news linked in the dataset allowed to identify also Italy (as location of predicate offences – usury and extortion related to mafia association Camorra) and Bulgaria and Panama (as further locations of money laundering).

Table A1 – Excerpt of Lexis Nexis World Compliance database. (Example related to individual ID 10399874)

Ent. ID	10399874
Name	Emilio
Surname	Izzo
Entry category	Adverse Media
Entry sub-category	Money laundering
Position	Sentenced to four years and six months for money laundering, extortion and usury – December 04, 2019.
DOB	1969
POB	-
Country	Italy
Remarks	According to giornalesm.com and libertas.sm; December 05, 2019: On December 04, 2019 a San Marino court sentenced Emilio Izzo and his associate, to four years and six months for money laundering, extortion and usury. According to the prosecution, EUR 2,400,000 were transferred and hidden at a **San Marino** bank by the suspect, money believed to be of illicit origin and linked to the **Camorra mafia**. A seizure of over EUR 1,900,000 took place a few days later and a total fine of EUR 9300 was also imposed.
Source	http://www.libertas.sm/notizie/2019/05/08/estorsioni-della-camorra-e-denaro-riciclato-sul-titano.html; https://web.archive.org/web/20191206125256/http://web.archive.org/screenshot/; http://www.libertas.sm/notizie/2019/09/20/san-marino-riciclaggio-di-denaro-frutto-di-estorsioni-della-camorra-partito-il-processo.html; https://web.archive.org/web/20191206124752/ http://web.archive.org/screenshot/ https://giornalesm.com/riciclaggio-condannata-coppia-di-coniugi-estorsioni-della-camorra-e-denaro-riciclato/; http://www.libertas.sm/notizie/2019/12/05/san-marino-condannata-una-coppia-per-riciclaggio-di-denaro.html; http://www.libertas.sm/notizie/2019/12/05/san-marino-riciclaggio-di-denaro-della-camorra-coniugi-condannati-antonio-fabbri.html; https://www.tripmondo.com/italy/campania/provincia-di-caserta/caserta/

Table A2 – Excerpt from the news linked in LN WoCo dataset (Example related to individual ID 10399874)

Text	"[…] Milioni di euro ritenuti provento di **associazione camorristica, estorsione usura e reati tributari "ripuliti" sul Titano**. Del riciclaggio di imponenti somme dovranno rispondere due coniugi, Emilio Izzo, cinquantenne di San Felice a Cancello, in provincia di Caserta, e la moglie, Monica Di Nuzzo, anche lei cinquantenne, residente in Bulgaria e domiciliata in Italia presso il marito. Secondo l'accusa il giro di soldi sporchi comincia dal 2001, quando attraverso 36 operazioni per la somma complessiva di 2.200.614,18 euro sono stati versati contanti su libretti al portatore, che all'epoca erano ancora legali ed erano stati accesi presso la Cassa di Risparmio […]. "[…]. Poi seguirono prelievi, movimentazioni e bonifici tra cui uno di 100mila euro a favore di una **società di Panama per l'acquisto di un appartamento**, almeno questo riportava la causale, nel paradiso fiscale del Centroamerica […]". "[…] Ancora i denari vennero investiti in certificati di deposito presso Cassa di Risparmio fino a che, il 21 novembre del 2016, di due coniugi hanno chiesto il trasferimento delle somme, per un ammontare pari a 1,9 milioni di euro, su un conto aperto a nome di Monica Di Nuzzo presso un **istituto di credito della Bulgaria** […]"

Table A3 – Processing and classification of the extracted information. (Example related to individual ID 10399874)

Associate/predicate offences	
[…]	0
extortion	1
usury	1
tax crimes	1
organised crime	1
of which, mafia-type	1
[…]	0
j-countries as money laundering location (ML_cases_j)	
[…]	0
Bulgaria	1
[…]	0
Panama	1
[…]	0
San Marino	1
[…]	0
j-countries as locations of associate/predicate offences ($other\_crimes_j$)	
[…]	0
Italy	1
[…]	0

b. Operationalisation of official AML/CTF blacklists into scores

Table A4 shows how official AML/CTF blacklists (which are 'dummy' variables, in the sense that a country may be included or not in a blacklist) are translated into scores so as to allow for measurement and correlation analysis (see Section 4).

Table A4 – Operationalisation of official blacklists into scores

Variable name	*Description*	*Possible values*
FATF_BL_2000_2006	Score related to the presence of a country in FATF list of Non-Cooperative Countries or Territories (NCCTs) in the 2000-2006 period;	Ranging from 0 to 1 where 0 = the country has never appeared in the list and 1 = the countries was in the list for the whole period;
FATF_BL_2008_2020	Score related to the presence of a country in FATF list of "High-Risk Jurisdictions subject to a Call for Action" (previously entitled "Public Statement") in the 2008-2020 period;	Ranging from 0 to 1 where 0 = the country has never appeared in the list and 1 = the countries was in the list for the whole period;
FATF_GL_2008_2020	Score related to the presence of a country in FATF list of "Jurisdictions under Increased Monitoring" (previously entitled "Improving Global AML/CFT Compliance: On-going process") in the 2008-2020 period;	Ranging from 0 to 1 where 0 = the country has never appeared in the list and 1 = the countries was in the list for the whole period;
FATF_Tech_compliance	Score related to FATF evaluation criteria 'Technical compliance'	Ranging from 0 to 1 where 0 = the country is evaluated as Compliant (C) for all the 40 Recommendations, and 1 = the country is evaluated as Non-compliant (NC) for all the 40 Recommendations.
FATF_Effectiveness	Score related to FATF evaluation criteria 'Effectiveness'	Ranging from 0 to 1 where 0 = the country is evaluated as Highly Effective (HE) for all the 11

		Immediate Outcomes, and 1 = the country is evaluated as Low Effective (LE) for all the 11 Immediate Outcomes.
INCSR_2008_2020	Score related to the presence in US INCSR list of 'major money laundering countries' in the 2008-2020 period.	Ranging from 0 to 1 where 0 = the country has never appeared in the list and 1 = the countries was in the list for the whole period;

c. Principal component analysis

The aim of the PCA is to explain the variance in the observed data through a smaller number of PC (sometimes referred to as 'factors'), which are linear combinations of the original data (Dunteman, 1989; Jolliffe, 2002; OECD & JRC, 2008). Specifically, these components have the property of being uncorrelated (orthogonal), which indicates that they measure different statistical dimensions, or underlying factors. In formula:

$$Z_1 = b_{11}x_1 + b_{12}x_2 + \cdots + b_{1Q}x_Q$$

$$Z_2 = b_{21}x_1 + b_{22}x_2 + \cdots + b_{2Q}x_Q$$

…

$$Z_Q = b_{Q1}x_1 + b_{Q2}x_2 + \cdots + b_{QQ}x_Q$$

Where:

Q = number of variables *x* in the dataset, which are used to operationalise the risk dimensions *proximity*, *opacity* and *security*;

$Z_1, Z_2, \ldots, Z_Q$ = principal components (PC);

$b_{11}, \ldots, b_{QQ}$ = component loadings (or factor loadings), which measure the association between variables *x* and the relevant component, and are chosen so as the principal components $Z_1, Z_2, \ldots, Z_Q$ are uncorrelated (orthogonal) and each one explains a share of the overall variance of the dataset.

When carrying out the PCA it is assumed that there are a number of *N*<*Q* components capable of both explaining a good share of the variance in the original data and capturing most of the information contained therein. This explains why the PCA has been frequently used in social research to describe multi-dimensional phenomena, which are difficult to observe via a single measure.

In this paper, the PCA is employed for two specific purposes: (a) to confirm the conceptual framework presented above, i.e. risk as a function of *three components* – proximity, opacity, and security; (b) to suggest a more sound and objective way to combine together and weight the single variables used to operationalise the three risk dimensions, in order to be able to calculate the composite indicator. Specifically, with regard to the second issue, the composite indicator was constructed as the weighted average of the scores extracted for each observation for the *N* identified components, using as weights the proportion of variance that can be explained by each component.[17] In other words:

$$ML\_index_{ij} = g(P_{ij}; O_j; S_j) = \alpha_1 z_{ij1} + \alpha_2 z_{ij2} + \cdots + \alpha_N z_{ijN}$$

Where:

i = reference country (in the case of the empirical application, Italy);

j = 1,…,*J* countries, with $j \neq i$;

N = number of PC ultimately retained, with $N < Q$;

$\alpha_1, \ldots, \alpha_N$ = the proportion of the variance in the model that can be explained by each component;

$z_{ij1}, \ldots, z_{ijN}$ = relevant value extracted by the PCA for each country *j* and for each component.

[17] Other functional forms of the indicator different from the weighted average were tested, especially for the purpose of conducting the sensitivity analysis and running the regressions. A version of the indicator was calculated using the geometric mean of the components (see Model AQ in the sensitivity analysis). It was highly correlated (r >.95) with the reference model (Model AW, see section 4.4). In the regression, a semi-log model was tested after log-transforming the scores of the three PCs constituting the indicator. Again, results did not change in a sensitive manner.

d. Sensitivity analysis: alternative models tested in the PCA and criteria/parameters employed

Table A5 illustrates the 21 models tested in the analysis, each of them producing an indicator of ML risk (Model AW is the one producing the indicator presented in the paper). Table A6 reports the correlation among all the 21 models. Correlation is always higher than .95.

Table A5 – Alternative PCA models tested in the sensitivity analysis

	Model	Description	Top 5 countries	No. PC	PC weights	Rotation	Normalisation	Reference year	N. Obs
1	MODEL_A	all hypothesised variables	SM, LU, NL, AT, CH	3	NO	Varimax	Min-max (0-1)	Last available year (LAY)	164
2	MODEL_AW	all hypothesised, weighted	SM, LU, NL, AT, CH	3	YES	Varimax	Min-max (0-1)	Last available year (LAY)	164
3	MODEL_AZ	all hypothesised, z-score stand.	SM, LU, NL, AT, CH	3	NO	Varimax	Z-score	Last available year (LAY)	164
4	MODEL_AZW	all hypothesised, z-score stand. weighted	SM, LU, NL, AT, CH	3	YES	Varimax	Z-score	Last available year (LAY)	164
5	MODEL AP	all hypothesised, Promax rotation	SM, LU, NL, AT, CH	3	NO	Promax	Min-max (0-1)	Last available year (LAY)	164
6	MODEL APW	all hypothesised, Promax, weighted	SM, LU, NL, AT, CH	3	YES	Promax	Min-max (0-1)	Last available year (LAY)	164
7	MODEL AQ	all hypothesised, geometric mean of PC	SM, LU, NL, AT, MT	3	NO (aggr: Geo. Mean)	Varimax	Min-max (0-1)	Last available year (LAY)	164
8	MODEL AL	all hypothesised, *cash_supply*, *complexity* and *unavailability* are log-transformed	SM, AT, NL, LU, MT	3	NO	Varimax	Min-max (0-1)	Last available year (LAY)	157
9	MODEL ALW	all hypothesised, *complexity*, *unavailability* and *cash_supply* log-transformed	SM, AT, NL, FR, LU,	3	YES	Varimax	Min-max (0-1)	Last available year (LAY)	157
10	MODEL A1418	all hypothesised, mean 2014-2018	SM, LU, NL, AT, MT	3	NO	Varimax	Min-max (0-1)	Average 2014-2018	164
11	MODEL_B	all hypothesised, 4 PC	SM, LU, NL, AT, MT	4	NO	Varimax	Min-max (0-1)	Last available year (LAY)	164
12	MODEL_BW	all hypothesised, weighted, 4 PC	SM, LU, NL, AT, MT	4	YES	Varimax	Min-max (0-1)	Last available year (LAY)	164
13	MODEL C	No GDP	SM, LU, NL, AT, CH	3	NO	Varimax	Min-max (0-1)	Last available year (LAY)	164
14	MODEL CW	No GDP	SM, NL, LU, AT, CH	3	YES	Varimax	Min-max (0-1)	Last available year (LAY)	164
15	MODEL D	No Rule of Law	LU, SM, NL, MT, AT	3	NO	Varimax	Min-max (0-1)	Last available year (LAY)	164
16	MODEL DW	No Rule of Law	SM, LU, NL, AT, MT	3	YES	Varimax	Min-max (0-1)	Last available year (LAY)	164
17	MODEL E	No Rule of Law	NL, LU, SM, AT, MT	4	NO	Varimax	Min-max (0-1)	Last available year (LAY)	164
18	MODEL EW	No Rule of Law	SM, NL, LU, AT, FR	4	YES	Varimax	Min-max (0-1)	Last available year (LAY)	164
19	MODEL F	*procedure_to_ start* is added	SM, NL, LU, AT, CH	3	NO	Varimax	Min-max (0-1)	Last available year (LAY)	162
20	MODEL FW	*procedure_to_ start is added*, PC are weighted	SM, LU, NL, AT, CH	3	YES	Varimax	Min-max (0-1)	Last available year (LAY)	162
21	MODEL G	all hypothesised, normalised 0-1, simple average (no PCA)	SM, AT, NL, LU, FR	No PCA	No PCA	No PCA	Min-max (0-1)	Last available year (LAY)	164

Notes: "all hypothesised variables" = distance_rec; contiguity; comm_ language; comm_currency; cash_supply; complexity; unavailability; GDP; bank_credit: rule_law. Model_AW = Model employed to produce the Indicator_AW presented in the paper

Table A6 – Correlation among ML risk indicators stemming from models tested in sensitivity analysis

	Index_a	*Index_aw*	*Index_ap*	*Index_apw*	*Index_al*	*Index_alw*	*Index_az*	*Index_azw*	*Index_a1418*	*Index_b*	*Index_bw*	*Index_c*	*Index_cw*	*Index_d*	*Index_dw*	*Index_e*	*Index_ew*	*Index_f*	*Index_fw*	*Index_g*
Index_a	1.000																			
Index_aw	0.999	1.000																		
Index_ap	1.000	0.999	1.000																	
Index_apw	0.999	1.000	0.999	1.000																
Index_al	0.951	0.954	0.953	0.956	1.000															
Index_alw	0.961	0.964	0.963	0.965	0.999	1.000														
Index_az	1.000	0.999	1.000	0.999	0.951	0.961	1.000													
Index_azw	0.999	1.000	0.999	1.000	0.954	0.964	0.999	1.000												
Index_a1418	1.000	0.999	1.000	0.999	0.951	0.961	1.000	0.999	1.000											
Index_b	0.999	0.997	0.999	0.997	0.952	0.961	0.999	0.997	0.999	1.000										
Index_bw	0.996	0.998	0.997	0.998	0.961	0.968	0.996	0.998	0.996	0.995	1.000									
Index_c	0.995	0.995	0.996	0.996	0.959	0.967	0.995	0.995	0.995	0.996	0.992	1.000								
Index_cw	0.995	0.996	0.995	0.997	0.960	0.968	0.995	0.996	0.995	0.993	0.993	0.999	1.000							
Index_d	0.976	0.974	0.976	0.974	0.907	0.918	0.976	0.974	0.976	0.976	0.969	0.959	0.958	1.000						
Index_dw	0.977	0.981	0.979	0.982	0.943	0.948	0.977	0.981	0.977	0.976	0.981	0.971	0.973	0.983	1.000					
Index_e	0.975	0.971	0.975	0.972	0.913	0.922	0.975	0.971	0.975	0.976	0.971	0.957	0.955	0.997	0.983	1.000				
Index_ew	0.973	0.977	0.975	0.978	0.945	0.948	0.973	0.977	0.973	0.973	0.982	0.965	0.967	0.978	0.997	0.983	1.000			
Index_f	0.991	0.991	0.991	0.991	0.954	0.962	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.954	0.966	0.955	0.965	1.000		
Index_fw	0.991	0.991	0.991	0.991	0.954	0.962	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.954	0.966	0.955	0.965	1.000	1.000	
Index_g	0.989	0.992	0.990	0.992	0.957	0.964	0.989	0.992	0.989	0.986	0.994	0.984	0.987	0.962	0.978	0.962	0.978	0.984	0.984	1.000

Notes: Pearson's correlation. All values were significant at 99.9% confidence level. Index_aw *is the indicator presented in previous paragraphs*

Source: Author's elaboration of various sources

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