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Joint Research Centre on Transnational Crime

UNIVERSITÀ CATTOLICA del Sacro Cuore

Co-funded by the Prevention of and Fight against Crime Programme of the European Union

Assessing the risk of money laundering in Europe

Final report of project IARM

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VU VRIJE UNIVERSITEIT AMSTERDAM

UNIVERSITY OF LEICESTER

Assessing the risk of money laundering in Europe

Final Report of Project IARM (HOME/2013/ISEC/AG/FINEC/4000005193)

www.transcrime.it/iarm

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Executive Summary

This study is the final report of **project IARM** (www.transcrime.it/iarm). IARM is co-funded by the Prevention of and Fight against Crime Programme of the European Union and it has been carried out by an international consortium coordinated by **Transcrime – Università Cattolica del Sacro Cuore** (Italy). Other **research partners** are:

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- the NPCC – National Police Chiefs' Council (United Kingdom)

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Bureau van Dijk provided support as data provider.

Objectives and methodology

Project IARM develops an exploratory methodology for assessing the risk of money laundering (ML). In particular, it develops a **composite indicator of money laundering risk**:

- at **geographic area** level
- at **business sector l**evel

The methodology is tested in three pilot countries (**Italy**, the **Netherlands** and the **United Kingdom**) and follows 7 methodological steps, which include:

- identifying ML risk factors across areas and sectors;
- operationalising risk factors into a set of proxy variables to allow measurement;
- combining the variables, through various statistical techniques, into a final indicator of ML risk;
- validating the indicator through a sensitivity analysis and comparison with other measures of ML.

IARM adopts a **quantitative approach** which complements the **qualitative perspective** of most existing national and supranational ML risk assessments (NRA and SNRA).

It responds to the need, stressed by regulatory developments at both EU and national level, to develop **objective and robust methodologies** for ML risk assessment.

Risk factors

In each of the three pilot countries, a country-specific set of risk factors is identified on the basis of:

- the relevant **international and national literature** (e.g. FATF guidelines, FIU reports, judiciary evidence, academic literature);
- **interviews with experts** (e.g. FIU officers, investigators, policy-makers, private sector);
- **data availability**: because it is not possible to find the same data and variables in all the three countries.

Risk factors are distinguished between **ML *threats*** and ***vulnerabilities***, as suggested by FATF and as depicted in Figures 1 and 2.

Figure E1 – ML risk factors analysed at sub-national area level (Italy and UK)

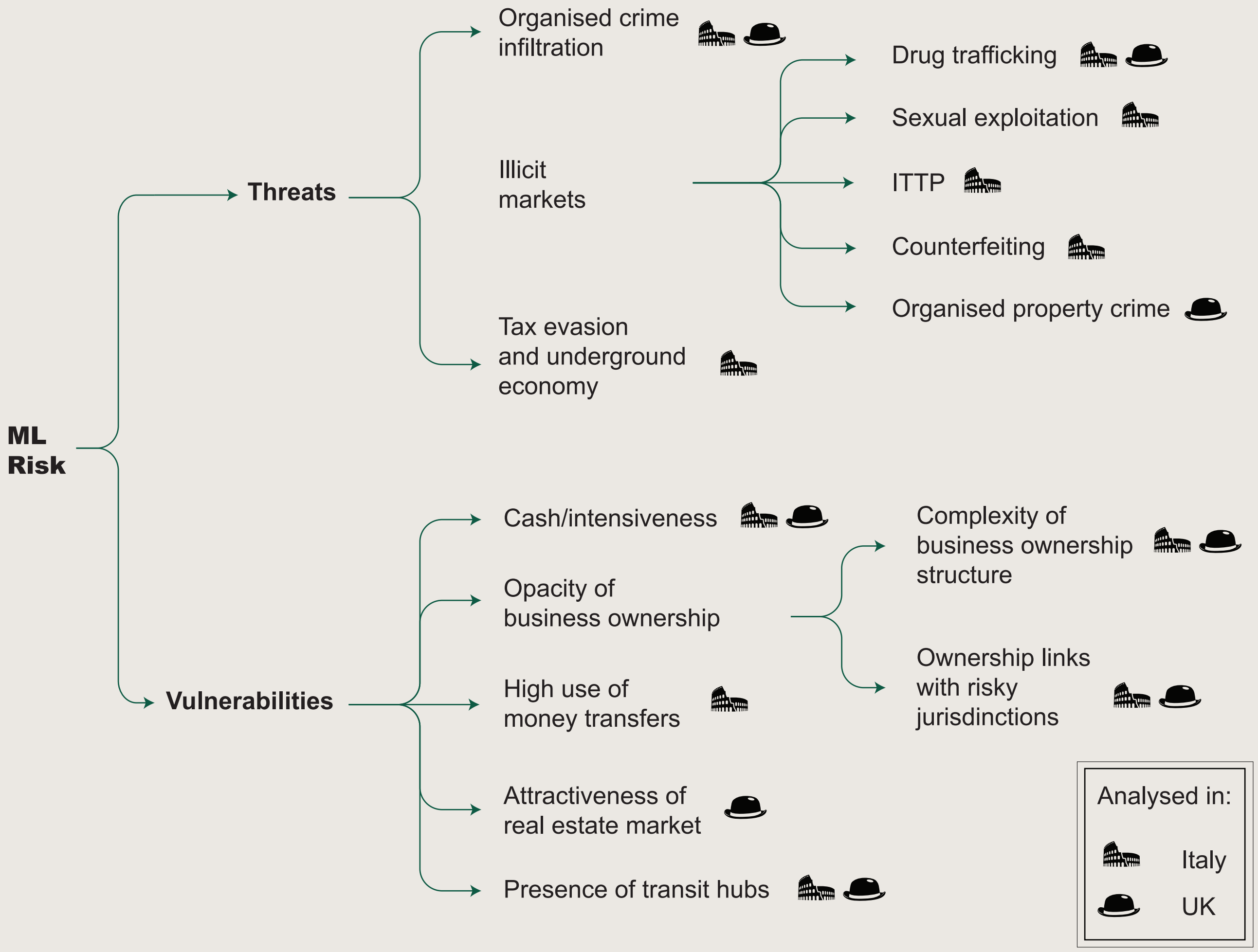
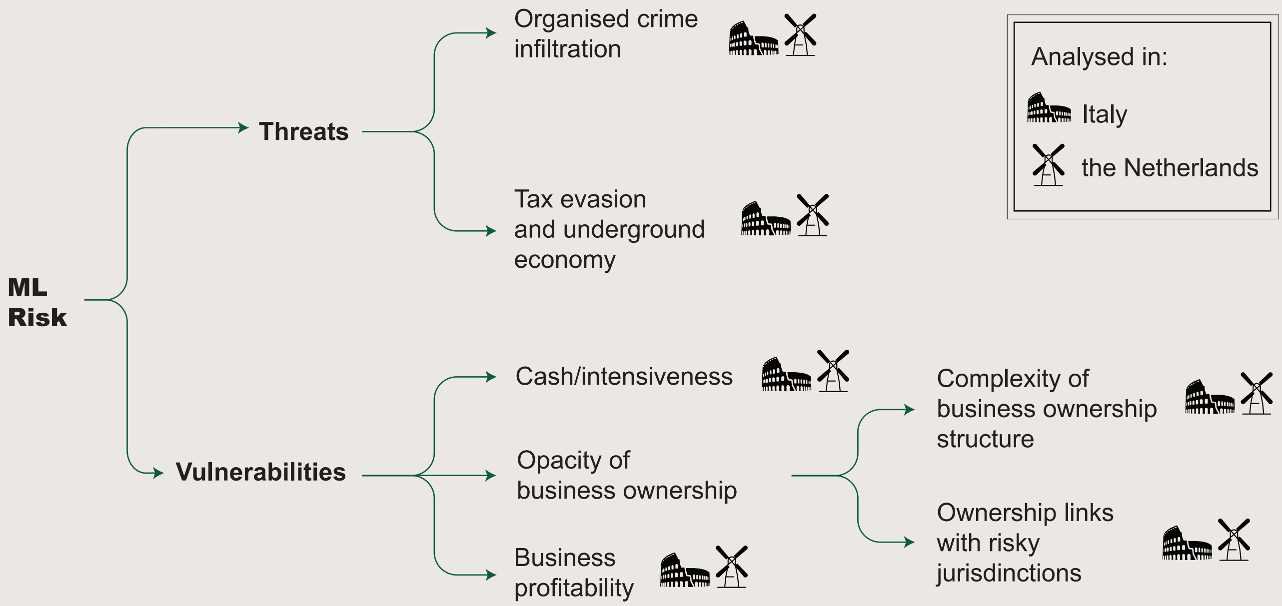


Figure E2 – ML risk factors analysed at business sector level (Italy and the Netherlands)



Italy

In Italy IARM assesses the ML risk across the **110 provinces and 77 economic sectors** (NACE divisions).

The analysis provides empirical support for the main findings of the **2014 National Risk Assessment** and of the **2016 FATF Mutual Evaluation Report**. It complements the NRA qualitative approach with a data-driven one, and supplements a regional analysis, while the NRA adopts only a national perspective.

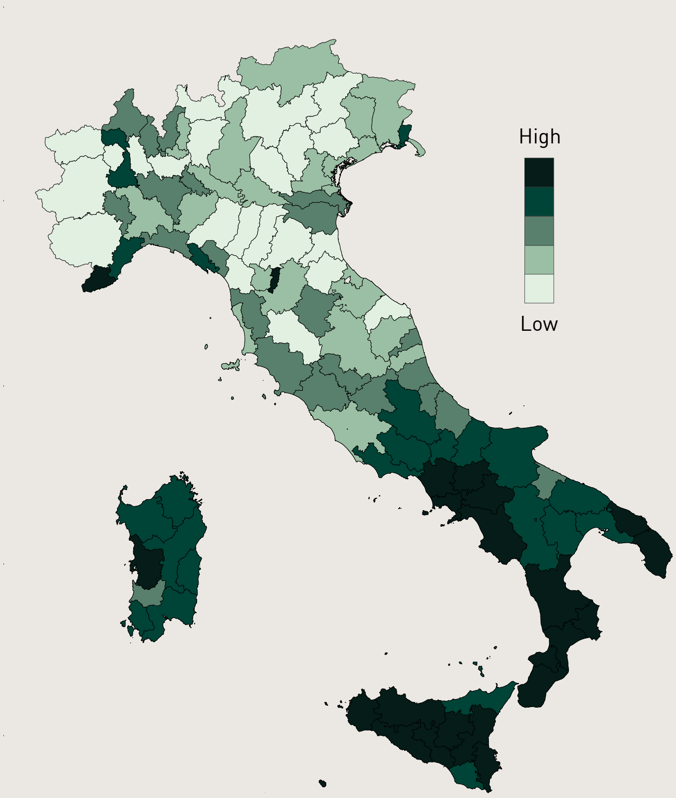
ML risk across provinces

The provinces with the highest ML risk (Figure 3) are in the south, with four Calabrian provinces ranking at the top (**Reggio Calabria, Vibo Valentia, Catanzaro, Crotone**). They record high levels of mafia-type infiltration, cash-intensiveness and underground economy.

In other southern regions, also **Napoli, Caserta, Palermo** and **Trapani** show high ML risk. Among non-southern regions, **Imperia and Prato** rank highest, showing relatively high levels of opacity of business ownership, of underground and cash-intensive economy and of money transfers.

At province level, ML risk is significantly **correlated with the rate of suspicious transaction reports (STRs)** – although some provinces seem to "under-report" with respect to their estimated level of risk.

Figure E3 - ML risk across Italian provinces



Top 12 provinces according to ML risk composite indicator

1. Reggio Calabria
2. Vibo Valentia
3. Catanzaro
4. Crotone
5. Napoli
6. Imperia
7. Caserta
8. Agrigento
9. Palermo
10. Caltanissetta
11. Trapani
12. Prato

Source: Transcrime - UCSC elaboration

ML risk across business sectors

At business sector level, analysis is made difficult by the **paucity of data** and of appropriate proxies. Therefore, only some **exploratory analysis** is carried out.

According to the composite indicator (Table 1), the economic sector with highest estimated ML risk in Italy are **bars and restaurants (NACE division I 56)**. They are characterised by high cash-intensiveness, irregular labour, opacity of business ownership and relatively high levels of organised crime infiltration.

They are followed by **other service activities** (NACE section S), which include a variety of businesses, from repair services, to personal service activities - like massage parlours, beauty centres and spas - but also security and investigation companies and fiduciary services.

The entertainment sector (Section R) also ranks highly. This not only includes **gambling and gaming activities** (R 92), such as casinos, VLT rooms (*sale slot*), but also related activities (in divisions R 90 and R 93), such as the management of **beach facilities, leisure activities** (e.g. racecourses) and **sporting associations**.

Several segments of the **construction supply-chain**, from sand extraction, to cement production, to building companies and relevant professional activities (e.g. engineering and architecture firms) rank among the first 20 most risky sectors, confirming the link between the construction industry, the underground economy and mafias' business cycle.

The high value of **travel agencies and tour operators** (N 79) is explained by the high cash-intensiveness and the close relationship with the tourism industry, which has proven to be vulnerable to criminal infiltration and money laundering activities.

Table E1 - ML risk across business sectors in Italy
Top 10 NACE divisions according to ML risk composite indicator

	Business sector (NACE division)	ML RISK COMPOSITE INDICATOR SCORE
	I 56. Food and beverage service activities	100.0
	S 95. Repair of computers and personal and household goods	80.4
Others	S 96. Other personal service activities	67.3
	N 79. Travel agency tour operator reservation service and related activities	64.4
	R 92. Gambling and betting activities	63.5
	R 90. Creative arts and entertainment activities	62.1
	P 85. Education	61.6
	A 03. Fishing and aquaculture	61.0
	M 74. Other professional scientific and technical activities	60.4
	C 19. Manufacture of coke and refined petroleum products	59.1

Source: Transcrime - UCSC elaboration

The Netherlands

In the Netherlands IARM assesses the ML risk across **83 economic sectors** (NACE divisions).

According to the composite indicator, the business sector with highest ML risk is **casinos, gambling and gaming businesses (R 92)**. Despite being under AML obligations, it shows evidence of OC infiltration, of 'cooking the books' activities and a high cash intensity and opacity of beneficial ownership. Also R 93 – which in the Netherlands includes **legal prostitution services** – and R 90 – which is related to art and entertainment activities – are in the top 10 sectors (see Table 2).

Also **hotels (I 55) and bars and restaurants (I 56)** rank highly. These sectors show high levels of OC infiltration, confirming their vulnerability to ML activities as suggested by the literature. **Security and investigation services (N 80)** also rank high, confirming evidence from the Dutch Police regarding involvement of organised crime in this business sector.

The analysis may provide inputs to the on-going **Dutch NRA (2017)**, supplementing its qualitative approach with a purely quantitative perspective. It could be used at both policy-making and investigative level, for example to better detect the economic activities to be placed under the **BIBOB screening** (an administrative measure to prevent OC infiltration).

However, the analysis should be further enhanced by improving the quality and availability of data, and by exploring further indicators and measurement approaches.

Table E2 – ML risk across business sectors in the Netherlands
Top 10 NACE divisions according to ML risk composite indicator

Business sector (NACE division)	ML RISK COMPOSITE INDICATOR SCORE
R 92. Gambling and betting activities	100.0
I 55. Accommodation	97.9
R 90. Creative, arts and entertainment activities	72.9
N 80. Security and investigation activities	69.8
S 95. Repair of computers and personal and household goods	54,4
N 79. Travel agency, tour operator reservation service and related activities	54.1
Others S 96. Other personal service activities	48.7
O 84. Public administration and defence; compulsory social security	46.6
R 93. Sports activities and amusement and recreation activities	44.0
I 56. Food and beverage service activities	43.8

Source: VU Amsterdam elaboration

United Kingdom

In the United Kingdom, IARM has assessed ML risk across the **43 police areas** in England & Wales. It was not possible, due to lack of workable data, to extend the analysis to Scotland and Northern Ireland. The **paucity of data** in relation to UK threats and vulnerabilities remains a significant issue, especially when trying to assess ML risk at business sector level.

The United Kingdom is at obvious risk from money laundering due to its position as a major **world financial centre**. This leads to a number of companies – especially in the City of London – with connections to **risky jurisdictions**.

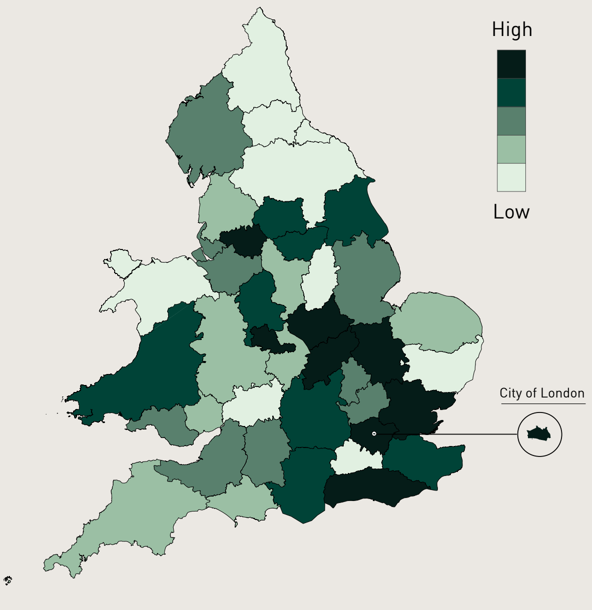
Among the three IARM countries, UK shows the **highest complexity of corporate structures**, with an average distance to beneficial owners[1] of 1.6 – which becomes 3.7 and 3.4 in the Channel Islands and Isle of Man respectively.

A number of other ML threats and vulnerabilities could also be identified across UK areas – such as the number of **organised crime groups** operating, the volume of predicate offences and **cash-intensiveness** of businesses.

According to IARM analysis, the **City of London** emerges as the area with the highest ML risk – representing an outlier in most of the considered variables. Conurbations such as the **Metropolitan Police area**, **Greater Manchester** and the **West Midlands** also emerge as high risk areas. These locations appear to be most exposed to serious and organised crime, to businesses' connections with risky jurisdictions and with the highest cash-intensiveness.

Although the approach outlined here is a pilot, it could be used to complement the **2015 UK ML NRA** and to support future National Risk Assessments. The risk-factors approach adopted by IARM could lead to a **more transparent methodology** to be developed to measure territorial and business level risks.

Figure E4 – ML risk across UK police areas of England & Wales (all 43 areas)



Source: University of Leicester elaboration

1. BOs in the BvD definition are the individual(s) who ultimately own or control a company or other legal entity. BvD identifies them by reconstructing the ownership chain until finding natural persons holding above a certain shareholding. For the purpose of this study, it has been decided to set the minimum threshold at 10% of the shareholding at the first level of the company ownership chain and 10% at further levels. The threshold adopted is lower than that indicated by the current EU Directive's definition (25% threshold) but allows for a more comprehensive analysis. When BO distance equals 1, the company is directly controlled by its BO(s) (see Annex for details).

Opacity of business ownership

Thanks to the use of an innovative set of data and proxies, IARM also carries out the first in-depth analysis of the degree of **opacity of business ownership** in Italy, the Netherlands and the UK.

Italian companies exhibit more direct control patterns: **BO distance** is lower than in the Netherlands and the UK (respectively 1.3, 1.7 and 1.6) and also the volume of connections with **risky jurisdictions** (such as off-shore countries) is more limited. However, figures vary greatly across areas and economic activities.

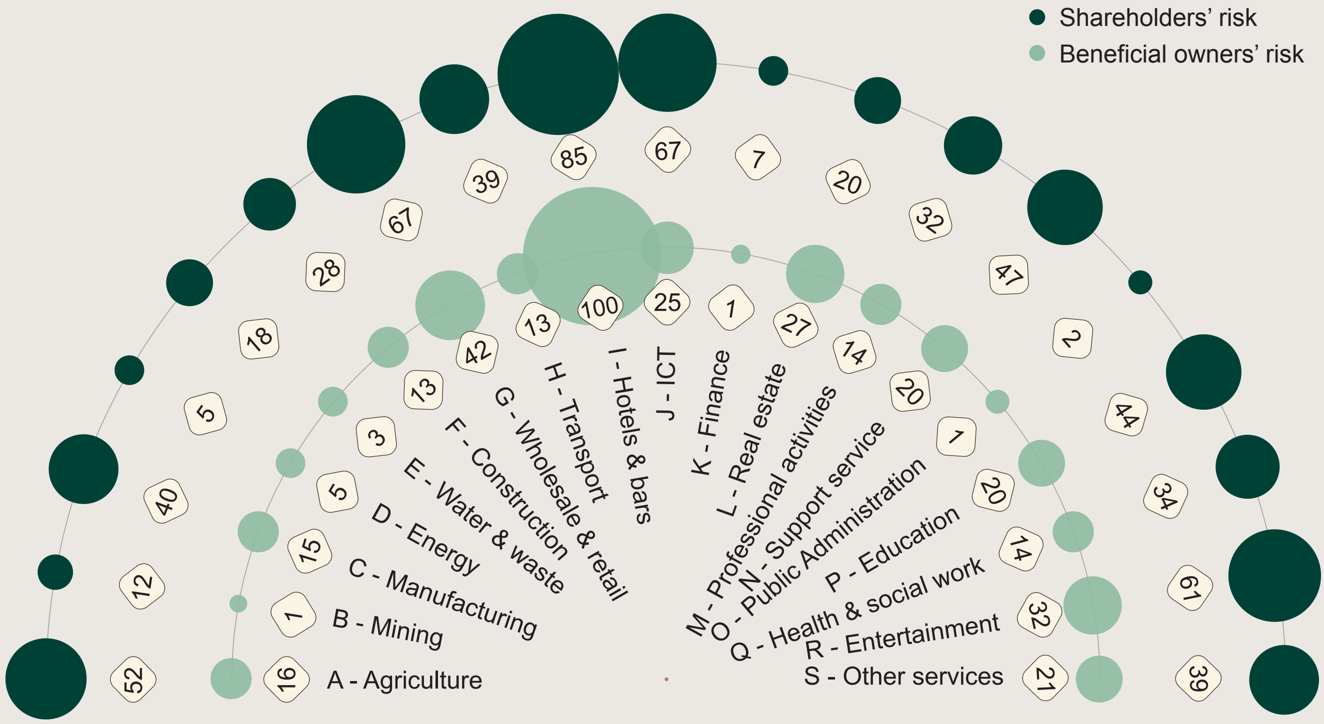
Business sectors like mining (NACE section B), energy (D), water and waste (E) and finance (K) are characterised by higher complexity and opacity in all the three countries, but also by a higher number of **multinational companies**.

After controlling by company size, **hotels, bars and restaurants** (section I), **entertainment & gaming** (R) and **other services** (S) emerge promptly. In the UK, **real estate businesses** (L) also rank high, highlighting the risk of a link between the UK property market and companies/individuals from opaque jurisdictions.

Some other statistics would deserve further research – for example the high number of shareholders (especially legal persons) from **Luxembourg, Cyprus** and **Switzerland** and of beneficial owners from **Spain** (in all the three countries, but especially in some southern Italian areas and sectors like R 92 - gambling & betting).

Figure E5 – Average distance to beneficial owners (min=1)

Figure E6 – Shareholders' and BOs' links with risky jurisdictions by business sector
Weighted by average company size. Average score of Italy, the Netherlands and UK. 100=max risk score



Research and policy implications

IARM added value

The IARM methodology builds on **FATF guidelines**. It does not intend to replace the qualitative approach of current ML national and supranational risk assessments (NRA and SNRA) but to complement it with a **quantitative and data-driven perspective**. With respect to existing risk assessment, IARM offers:

- a higher disaggregation detail (e.g. a regional perspective vs the national perspective of most NRAs);
- coverage of all business sectors (while NRA usually do not adopt a sectorial perspective);
- an innovative analysis of business ownership opacity;
- a synthetic measure of a complex phenomenon such as ML risk.

The indicators of ML risk developed by IARM could be **adopted in the operational domain** by both public agencies and private entities, for example:

- by policy-makers, to support a better allocation of AML resources and measures across the areas and sectors based on their risk level;
- by investigative agencies (e.g. LEAs and FIUs), to identify the areas and sectors on which to strengthen monitoring and investigations;
- by obliged entities (e.g. banks, professionals, etc.), to enrich the set of indicators and red-flags to be used in AML customer due diligence.

Future challenges

IARM is only a **first step** towards a systematic assessment of ML risks across areas and businesses. It follows an **exploratory methodology** which is affected by **data availability** – it works better in contexts characterised by richer set of information, while it will underestimate those risk factors for which data are still lacking (like emerging ML risks which by definition lack estimates).

In order to improve this approach, **data quantity and quality** should be enhanced. In particular:

- at business sector level;
- on important ML threats such as **tax crimes and fraud**;
- on important ML vulnerabilities such as **cash use**, for which statistics are available in most EU countries only at the national level;
- on the **ownership structure** of European businesses;
- on suspicious transaction reports/suspicious activity reports (**STRs/SARs**) which could be rich sources of information but are only partially exploited for research purposes

The **IARM data-driven methodology** should be combined with the qualitative approach of other NRAs in order to obtain a comprehensive understanding of ML risks. It should be **replicated in other countries**, both in Europe and abroad, to test its validity and refine the methodology. Moreover, it should take into consideration other factors (e.g. vulnerabilities in AML regulation).

The benefits would go much beyond the AML field, reinforcing also the fight against **terrorist financing, tax evasion** and **corruption** and improving the efficiency and security of the EU internal market.

Acronyms

ABI – Associazione Bancaria Italiana (Italian Banking Association)
AML – Anti-money laundering
AMLD – Anti-money laundering directive
ANAC – Autorità Nazionale Anticorruzione (National Anti-Corruption Authority – Italy)
ANBSC – Agenzia Nazionale per l'amministrazione e la destinazione dei Beni Sequestrati e Confiscati (Italian agency for the recovery and management of seized and confiscated assets)
ARO – Asset Recovery Office
ATM – Automated teller machine
BEIS – Department for Business, Energy & Industrial Strategy (United Kingdom)
BIBOB – Wet ter Bevordering Integriteitsbeoordelingen door Het Openbaar Bestuur (The Public Administration Probity Screening Act – the Netherlands)
BO – Beneficial owner
BvD – Bureau van Dijk
CBS – Centraal Bureau voor de Statistiek (Central Agency for Statistics – the Netherlands)
CDD – Customer due diligence
CFT – Combating the financing of terrorism
CONSOB – Commissione Nazionale per le Società e la Borsa (Italian Securities and Exchange Commission – Italy)
CSC – Centro Studi Confindustria (Confindustria Research Center – Italy)
CSF – Comitato di Sicurezza Finanziaria (Financial Security Committee – Italy)
CVS – Commercial victimisation survey
DIA – Direzione Investigativa Antimafia (Anti-mafia investigation agency – Italy)
DNA – Direzione Nazionale Antimafia (Anti-mafia Prosecutors' Office – Italy)
DNFBPs – Designated non-financial businesses and professions
DPA – Dutch Payment Association
EC – European Commission
ECB – European Central Bank
ECOLEF – The Economic and Legal Effectiveness of Anti Money Laundering and Combating Terrorist Financing Policy (Research project)
EBITDA – Earnings before interests, taxes, depreciation and amortization
EMCDDA – European Monitoring Centre for Drugs and Drug Addiction
ESA – European supervisory authorities
EU – European Union
EURODAD – European Network on Debt and Development
FATF – Financial Action Task Force
FDI – Foreign direct investments
FIOD – Fiscale inlichtingen en opsporingsdienst (Fiscal information and investigation service – The Netherlands)
FIU – Financial intelligence unit
FSI – Financial Secrecy Index
FSS – Secrecy Score of the Financial Secrecy Index
GdF – Guardia di Finanza (Italy)
GDP – Gross domestic product
HMRC – Her Majesty's Revenue and Customs (United Kingdom)
IARM – Identifying and Assessing the Risk of Money laundering in Europe (Research project)

IMF – International Monetary Fund
ISO – International Organization for Standardization
ISTAT – Istituto Nazionale di Statistica (National Institute for Statistics – Italy)
IT – Information technology (or Italy depending on the context)
ITTP – Illicit trade in tobacco products
LEA – Law enforcement agency
MEF – Ministero dell'Economia e delle Finanze (Italian Ministry of Economy and Finance)
MER – Mutual evaluation report
ML – Money laundering
MONEYVAL – The Committee of Experts on the Evaluation of Anti-Money Laundering Measures and the Financing of Terrorism
MoRiLE – Management of Risk in Law Enforcement
MS – Member state
MTBs – Money transfer businesses
NACE – Nomenclature Générale des Activités Économiques dans les Communautés Européennes (Statistical classification of economic activities in the European Community)
NCA – National Crime Agency (United Kingdom)
NCC – Dutch Central Catalogue (the Netherlands)
NGO – Non-governmental organization
NL – the Netherlands
NPCC – The National Police Chiefs Council (United Kingdom)
NPM – New payment methods
NRA – National risk assessment
NUTS – Nomenclature of Territorial Units for Statistics
OC – Organised crime
OCG – Organised crime group
OCM – Organised Crime Monitor (Research project)
OCP – Organised Crime Portfolio (Research project)
ODCEC – Ordine dei Dottori Commercialisti e degli Esperti Contabili (Professional association of Certified Public Accountants, Auditors and Advisors – Italy)
OECD – Organisation for Economic Cooperation and Development
OPC – Organised property crime
OSCE – Organization for Security and Co-operation in Europe
PC – Principal component
PCA – Principal component analysis
PEP – Politically exposed person
POCA – Proceeds of Crime Act (United Kingdom)
POS – Point of sales
PPO – Public Prosecution Office (the Netherlands)
PSC – People with significant control
RBA – Risk-based approach
RF – Risk factor
ROE – Return on equity
ROA – Return on assets
SAR – Suspicious activities report
SNRA – Supra national risk assessment
SOCA – Serious organised crime agency United Kingdom)
SOCTA – Serious and Organised Crime Threat Assessment
STR – Suspicious transaction report
TBML – Trade based money laundering
TF – Terrorist financing
TI – Transparency International

TJN – Tax Justice Network
UCSC – Università Cattolica del Sacro Cuore Milano (Italy)
UIF – Unità di Informazione Finanziaria (Italian Financial Intelligence Unit – Italy)
UK – United Kingdom
ULEIC – University of Leicester (United Kingdom)
UN – United Nations
UNODC – United Nations Office on Drugs and Crime
VAT – Value added tax
VLT – Video lottery terminal
VU – Vrije Universiteit Amsterdam (the Netherlands)
WODC – Wetenschappelijk Onderzoek en Documentatiecentrum (Research and documentation Centre of the Dutch Ministry of Justice)
WWFT – Wetter voorkoming van witwassen en financieren van terrorisme (Dutch law on money laundering and terrorist financing)

Introduction

This study is the **final report of project IARM** – Identifying and Assessing the Risk of Money Laundering in Europe (www.transcrime.it/iarm). IARM is co-funded by the Prevention of and Fight against Crime Programme of the European Union, DG Home Affairs (HOME/2013/ISEC/AG/FINEC/4000005193).

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The objectives of IARM are:

- to develop a standardised methodology for money laundering risk assessment, and in particular a **composite indicator of ML risk**:
    - at sub-national regional level
    - at business sector level
- to test the indicator in three pilot countries: Italy, the Netherlands and United Kingdom.

IARM fits the current debate on money laundering risk assessment, and it complements existing assessment exercises at both national and EU supranational level. Beneficiaries of the project are **researchers, practitioners, institutions and private companies** in the AML field. IARM will help European public authorities and obliged entities (e.g. banks, professionals, real estate agencies, etc.) to develop more effective AML/CTF risk assessment policies and customer due diligence screenings.

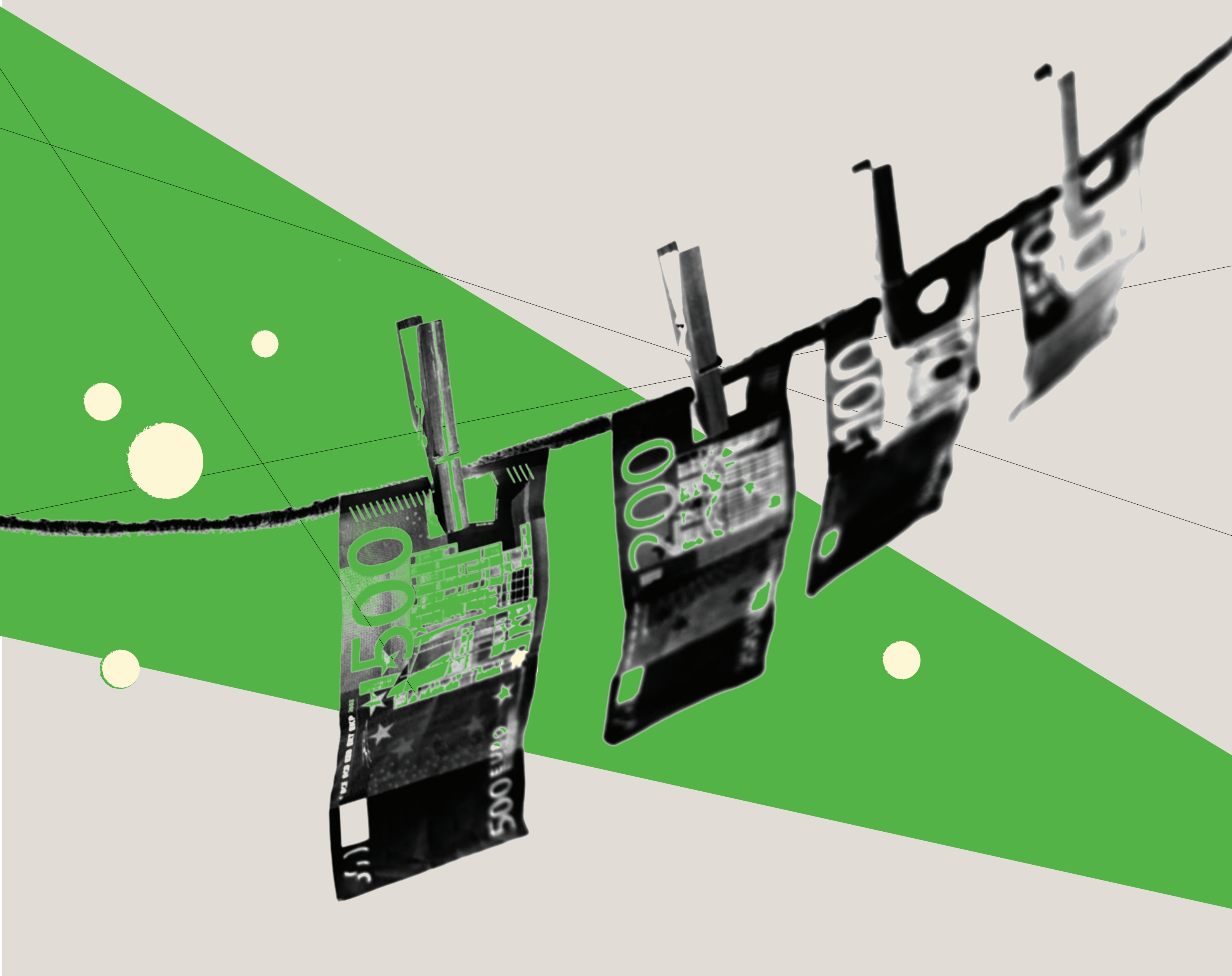
The report is structured as follows:

- **Chapter 1** describes the institutional, conceptual and methodological framework for ML risk and ML risk assessment;
- **Chapter 2** presents the results of the ML risk assessment in Italy;
- **Chapter 3** presents the results of the ML risk assessment in the Netherlands;
- **Chapter 4** presents the results of the ML risk assessment in the United Kingdom;
- **Chapter 5** focuses on the analysis of the opacity of business ownership across the three countries and economic sectors;
- **Conclusions** briefly discuss research and policy implications.

The **Methodological Annex** (available at the link http://www.transcrime.it/wp-content/uploads/2017/04/IARMAnnex.pdf) provides more details on the methodology and relevant legislation.

2. Support has been provided also by UK Home Office. See Acknowledgements section for the full list of people and institutions that have supported the project.

1. Money laundering risk assessment: the framework



1.1 Institutional framework

Risk-based approach

In the past twenty years the **risk-based approach** (henceforth RBA) has become the pivot of the AML/CFT regime worldwide. Key references for the RBA at international level are **FATF Recommendation 1** and its **Interpretative Note** (FATF, 2012 - see Annex for details). The basic principle of the RBA is simple:

- AML/CFT measures (e.g. due diligence on a bank's customer) should be "commensurate with the risks identified": higher risks require enhanced measures, lower risks allow simplified ones (FATF, 2012, pp. 11, 31);
- AML/CFT resources (e.g. the number of AML officers or FIU staff) should be allocated according to these risks: more resources where the risk is higher.

Risk assessment is the exercise which allows to identify the areas, sectors, operations, and subjects at higher risk (FATF, 2013a; ISO, 2009a, 2009b).

The risk-based approach in the EU regulatory framework

This approach is fully endorsed by the EU regulatory regime. **Directive 2015/849** (or Fourth AML Directive), and its following amendments and proposals for amendments are centred on the RBA concept:

> *"(22) The risk of money laundering and terrorist financing is not the same in every case. Accordingly, a holistic, risk-based approach should be used. The risk-based approach is not an unduly permissive option for Member States and obliged entities. It involves the use of evidence-based decision-making in order to target the risks of money laundering and terrorist financing facing the Union and those operating within it more effectively"* (Directive 849/2015 - EC, 2015).

In its Section 2 (*Risk assessment*), the Directive specifies that RBA and risk assessment should be performed:

- at the **supranational level**, to assess the ML/TF risks of the EU internal market and relative to cross-border activities (Article 6);
- at the **national level**, by each single EU MS (Article 7);
- by **obliged entities** (e.g. banks, professionals), as part of their CDD activity (Article 8 and Artt. 10-24).

In other words, EU proposes a **three-level approach** (European Commission, 2015): each level (e.g. obliged entities, national, supranational) should take account of the risk assessment conducted at other levels, so as to achieve the *holistic* nature advocated by the Directive.[3] The following paragraphs describe in detail how risk assessment is performed at the three levels, and discuss the current shortcomings and challenges of this approach.

Risk assessment at supranational, national and obliged entity level

Risk assessment at the supranational level

In line with Art. 6 of the Directive, the European Commission has been conducting a **Supranational Risk Assessment** (**SNRA**) with the aim of identifying and assessing supranational ML/TF risks, i.e. those which affect the internal market and are related to cross-border activities. The assessment is conducted by a working group led by EU Commission in cooperation with a variety of stakeholders, including:

3. Also FATF recommends that RBA be applied by both countries and obliged entities. In particular "countries should identify, assess and understand the ML/TF risks […] and should take action, including designating an authority or mechanism to coordinate actions to assess risks […]" (FATF, 2012, p. 6); and "financial institutions and DNFBPs should be required to take appropriate steps to identify and assess their ML/TF risks (for customers, countries or geographic areas; and products, services, transactions or delivery channels). […] [They] should be required to […] manage and mitigate effectively the risks" (FATF, 2012, p. 33)

- The EU Experts Group on Money Laundering and Terrorist Financing (EGMLTF)
- The European Supervisory Authorities (ESAs), namely the European Banking Authority, European Securities and Markets Authority, European Insurance and Occupational Pensions Authority
- EU FIUs
- Europol
- Eurostat
- FATF
- Other stakeholders, including representatives of obliged entities at EU level, NGOs, academics

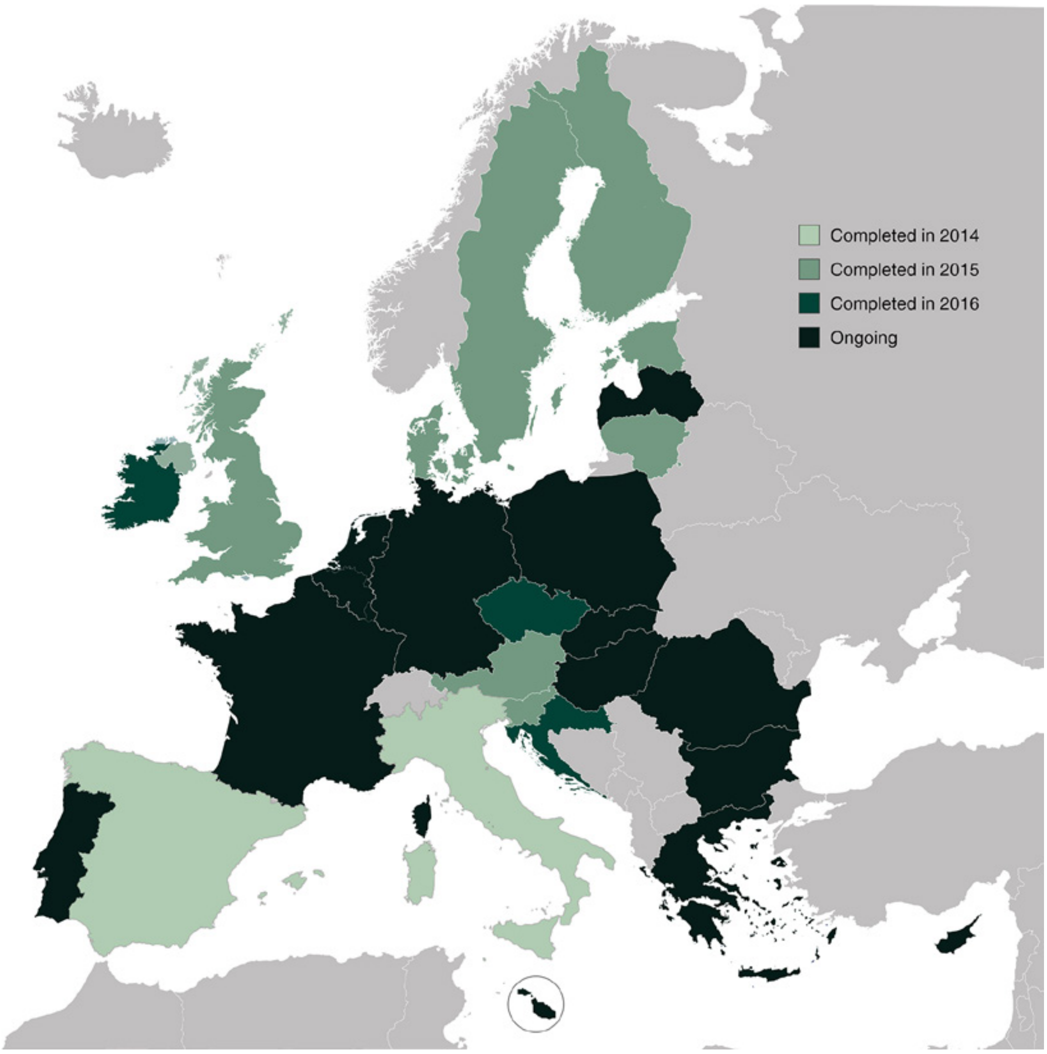
The SNRA report – which is expected by the **end of June 2017** and which must be **updated every two years** – will provide an overview of the ML/TF supranational risks. It will be based on the analysis of the "interplay of estimated threats and vulnerabilities for each type of *modus operandi*" (i.e. ML/TF exploitable mechanisms) (European Commission, 2015, p. 11), while consequences will not be covered (see below).

Risk assessment at the national level

In recent years, following FATF Recommendation 1 and Art. 7 of Directive 849/2015, numerous countries have undertaken **ML/TF National Risk Assessment (NRA)** processes. In most cases, they have been carried out in preparation of an upcoming FATF Mutual Evaluation (e.g. in Italy, Spain, Sweden, etc.).

The map below shows the current status of **NRA across EU member states** – some countries have NRA in progress while others have already published the NRA report. In response to FATF Rec. 1, also other countries outside Europe have undertaken the NRA process. They include the **United States** (2015), **Canada** (2016), **Japan** (2015), **Switzerland** (2015), **Singapore** (2013).

Figure 1 – Current status of NRA across EU Member States Updated at January 2017



Source: Transcrime-UCSC elaboration on various sources

Risk assessment at obliged entity level

The third level subject to ML/TF RBA and risk assessment obligations is that of **obliged entities** (e.g. banks, financial intermediaries, professionals, high-value dealers, etc. – for an official list at EU level see Directive 849/2015, Article 2 and relevant national legislation).

In recent years, numerous **risk assessment guidelines** have been issued by the **supervisory authorities** of each category of obliged entity at EU and national level. They include a long list of ML/TF risk factors and **anomaly indicators** to be taken into account when conducting CDD activity.[4]

In order to implement these guidelines, obliged entities have introduced a variety of measures, which include:

- appointment of dedicated personnel (e.g. **AML Risk Managers**, often cooperating with **Chief Risk Officers**);
- development and adoption of **ad hoc ML risk models and software**, which help in monitoring clients' risk and improving customer due diligence.

The adoption of these solutions has been greater for those obliged entities (like banks and financial institutions) which by their nature must manage **greater amounts of customers and transactions**, and it has been lower for other categories such as professionals, lawyers, notaries, high value dealers. The effectiveness of the AML risk models adopted varies widely even within the same industry.

The lack of harmonisation

Unfortunately, the increasing number of risk-assessment exercises is not accompanied by increasing harmonisation among the methods adopted. Despite the existence of **common guidelines** (e.g. those issued by FATF, IMF, World Bank, Sectors' Supervisory authorities – and those, in general, on risk assessment provided by ISO 31000), each country or entity seems to follow its **own RA methodology**.

As regards NRA by countries, most of them adopt a **qualitative approach** based more often on experts' assessments than on hard data.[5] A recent report by WODC (Veen & Ferwerda, 2016), as a pilot study for the Dutch NRA, has provided a comparative overview of five countries' NRA (Canada, Italy, Sweden, United Kingdom, United States), and it has shown the wide variety of the information, sources, and methods adopted. In particular, the report pointed out the **difficulties in replicating these methodologies in other contexts**.

Table 1– Comparison among 5 countries' ML NRA

Country	Followed FATF guidance?	Method	Risk quantification / classification?	Includes potential / unrecorded risks?	Replicable?
United States	Yes – with different taxonomy	Semi-quantitative	No	No	No
United Kingdom	Yes	Mostly qualitative	Classification	No	No
Canada	Yes	Qualitative	Classification	No	No
Italy	Yes	Semi-quantitative	Classification	No	In part
Sweden	Yes	Qualitative	Classification	No	No

Source: Veen & Ferwerda, 2016

4. See, for example, the guidelines issued by the Bank of Italy in April 2013 (Banca d'Italia, 2013) and the Dutch National Bank in 2015 (http://www.toezicht.dnb.nl/binaries/50-212353.pdf)

5. For a review of different risk assessment methods (qualitative, semi-quantitative, quantitative) see ISO 30001, p. 13.

Likewise, each category of **obliged entity** may interpret the risk assessment in a different way; and even within the same category (e.g. the banking industry) different stakeholders (e.g. different banking groups) may rely on different models, *modi operandi* and practical tools yielding very different analyses and risk maps.

Obviously, this is part of the exercise itself – **tailoring the risk assessment to the specific nature (and risks) of each area, sector, activity** (the activity of a bank is not the same as that of a small law firm, which entails different risks and assessment needs). However, the **lack of harmonised and data-based** RA methodologies makes it difficult:

- to replicate the risk assessment **over time;**
- to produce **comparative analyses** across countries, sectors, areas**;**
- to have **transparent, accountable and verifiable** methodologies**;**
- to accomplish a **"holistic approach"** as advocated by the European AML Directive (EC, 2015, para. 22).

Furthermore, it may produce **market distortions** – favouring the less compliant and less transparent assessors, in regard to both countries and obliged entities.

How IARM addresses these gaps

The development of the ML risk composite indicator by IARM follows a methodology which is:

- **transparent**
- **verifiable**
- **replicable,** because it is tested in different countries (Italy, the Netherlands, the UK) and extended to business sectors as well
- and allows **comparative analysis** over time and across areas.

The quantitative approach followed by IARM complements the qualitative method adopted by most NRA and SNRA. It helps to improve understanding of ML risks across areas and sectors and can support the everyday work of AML practitioners.

1.2 Conceptual framework

Before the IARM methodological approach is presented, it is necessary to provide some key definitions and concepts.

Money laundering (and terrorist financing)

IARM applies the definition of money laundering adopted at EU level and included in the Directive 849/2015/EC, Article 1:

> *3. For the purposes of this Directive, the following conduct, when committed intentionally, shall be regarded as money laundering:*
>
> *(a) the **conversion or transfer of property**, knowing that such property is derived from criminal activity or from an act of participation in such activity, for the purpose of concealing or disguising the illicit origin of the property or of assisting any person who is involved in the commission of such an activity to evade the legal consequences of that person's action;*
>
> *(b) the **concealment or disguise** of the true nature, source, location, disposition, movement, rights with respect to, or ownership of, property, knowing that such property is derived from criminal activity or from an act of participation in such an activity;*
>
> *(c) the **acquisition, possession or use** of property, knowing, at the time of receipt, that such property was derived from criminal activity or from an act of participation in such an activity;*
>
> *(d) **participation in**, association to commit, attempts to commit and aiding, abetting, facilitating and counselling the commission of any of the actions referred to in points (a), (b) and (c).*
>
> *4. Money laundering shall be regarded as such even where the activities which generated the property to be laundered were carried out in the territory of another Member State or in that of a third country.*

The focus of IARM is on **money laundering**, rather than **terrorist financing.** The main reason is that – although these offences are often addressed by the same regulatory measures – they are completely different phenomena which require separate analysis of threats and vulnerabilities, as also recommended by FATF (FATF, 2013a, p. 10).

Not by chance, recent NRAs (like the Dutch one) try to avoid conducting a single risk assessment encompassing both ML and TF risks, while they keep the two exercises separate (Veen & Ferwerda, 2016). The EU SNRA is evaluating each risk factor and *modus operandi* with reference to respectively the risk of ML and of TF – although the assessment often leads to the same risk score (European Commission, 2015).

Nevertheless, some ML risk factors **apply also to terrorist financing**: for example, the level of cash-intensiveness or the opacity of certain legal persons may be exploited both by criminals wanting to launder money or by criminals funding terrorist groups. Assessing their likelihood furnishes better understanding of TF risks as well.

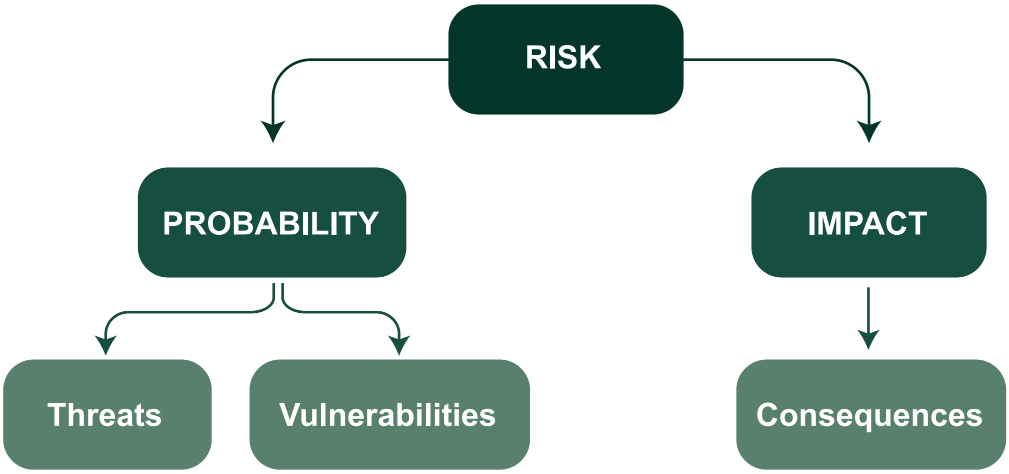
Money laundering risk and risk factors

In the risk assessment/risk management domain, risk is usually defined as a function of two elements (ISO, 2009b, p. 1):

- the **probability** (or **likelihood)** that the event/phenomenon will occur;
- the **impact (or consequences)** which it would generate.

This concept applies to an almost infinite variety of risk types: from **earthquakes** (the probability of an earthquake happening times the damage which it could produce) to **credit risk** (e.g. the likelihood of credit default and its possible consequences on the economy, society, etc.). And it applies also to money laundering. FATF defines **ML risk** "as a **function of three factors: threat, vulnerability and consequence"** (FATF, 2013a, p. 8), where threats and vulnerabilities concur in determining the *probability* of ML.

Figure 2 - Money laundering risk



Analysis of these three risk factors (or *risk dimensions* in the IARM taxonomy) – threats, vulnerabilities, consequences – is therefore at the core of any ML risk assessment.[6] But what do they mean exactly? They are briefly defined here, while section 1.4 and Annex A1 will provide an in-depth discussion and review.

Threats

ML threats are **people or activities** that may need to launder money (FATF, 2013a, p. 7; Dawe, 2013, p. 112):[7] for example, criminal groups involved in drug trafficking or tax crimes which have accumulated dirty funds. In other words, threats are related to the scale of **ML predicate offences** which generate illicit proceeds others (see below section 1.4).

Vulnerabilities

In the ML domain, vulnerabilities are **the factors which attract, facilitate or allow money laundering** to happen. In other words, they are those factors which may be exploited by threats (FATF, 2013a, p. 7): for example, high levels of cash diffusion or the presence of weaknesses in the AML legislation. According to 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). Indeed, the list of direct and indirect ML vulnerabilities could be almost endless (**FATF identifies more than 60 vulnerabilities** – see below for details).

Consequences

Consequences concern the **impact or harm that ML (or TF) events may produce** on the economy, society and financial markets. They can be related to "cost, damage caused, […] effect on financial systems and institutions and jurisdictions more generally" (Dawe, 2013, p. 113). They can be short- or long-term consequences; they can be direct or indirect; and they can be associated with the ML process itself or result from the use of the assets that are then successfully laundered (Dawe, 2013; FATF, 2013a). Provided below is a detailed review based on Ferwerda (2013) and Unger (2007).

6. In the FATF's words, ML risk assessment requires "making judgments about threats, vulnerabilities and consequences" (FATF, 2013c, p. 8).

7. As defined by Dawe (2013, p. 112), "a threat is largely related to the nature and scale of potential demand for ML".

Defining the unit of risk assessment

The concept of ML risk assessment may apply to a **variety of levels or units of analysis** (FATF, 2013a, p. 4; Wolfsberg Group, 2015, p. 7), e.g.:

- countries (i.e. the risk that a country may be misused or affected by money laundering)
- regions
- economic sectors
- services (e.g. the intermediation service offered by a real estate agency)
- transactions or products (e.g. cash deposits at ATMs, bank cheques, etc.)
- persons (i.e. the risk that a certain company or natural person may be misused, affected or may conduct ML activities)

Although the concepts of *threats, vulnerabilities* and *consequences* apply to all of these levels, the **identification of risk factors can change** according to the unit of analysis chosen (FATF, 2013a, p. 22).

For example, if the assessment is conducted at sub-national regional level, some vulnerabilities related to the weaknesses in the ML legislation do not apply because different regions of the same country are generally subject to the same regulatory regime. Similarly, some *threats* which may be considered in a territorial assessment (e.g. the amount of revenues locally generated by drug markets) become meaningless when the perspective is at business sector level.

Other risk factors, such as *cash-intensiveness*, apply to all units of analysis, but they are declined into different forms: e.g. cash-intensive territories may be defined as those where the diffusion of cash as means of payment is higher; cash-intensive business sectors may be those where the weight of cash on total assets is higher; cash-intensive persons are those who perform/receive more payments in the form of cash, etc. Defining the unit of assessment is therefore a crucial preliminary step for any ML risk assessment.

1.3 Methodological framework: the IARM approach

From risk factors to a composite indicator of ML risk

The idea behind the IARM study, in line with the FATF conceptual framework, is that **the overall ML risk of a certain area or business sector is a function of the level of the risk factors** in that area or sector. Building on this approach, and on the risk assessment methodologies applied in previous NRAs, IARM develops a measure of ML risk:

- at sub-national regional level, i.e. across regions in the same country
- at business sector level

It tests this approach in **Italy** (in the 110 provinces and in NACE business sector divisions), the **Netherlands** (in the NACE business sector divisions) and in the **United Kingdom** (in the 43 police areas of England & Wales).

To do so, IARM identifies, in each of these areas/sectors, a variety of **risk factors** grouped as *threats* and *vulnerabilities* as defined above. It transforms them into proxies so as to allow measurement, and it combines the factors, through a range of statistical techniques, into a **composite indicator** representing a synthetic measure of **ML risk** at area or sector level.

Given the difficulties of measurement, **consequences are not considered in the analysis** and they are not covered by the final indicator. This choice is in line with previous NRAs and with the EU SNRA.[8] Indeed, the FATF RA guidelines suggest that "countries may opt to focus primarily on […] understanding threats and vulnerabilities" (FATF, 2013a, p. 8).[9]

The IARM methodological approach can be better illustrated in **7 steps**.

This 7-step process follows the **OECD guidelines for the construction of composite indicators** (OECD & JRC, 2008) and previous works aimed at producing indicators of criminal phenomena, in particular organised crime (see, e.g., Dugato, De Simoni & Savona, 2014; Transcrime, 2013; Calderoni, 2011; Van Dijk, 2007). The process also follows the three stages defined by FATF as part of the risk assessment process (FATF, 2013, p. 21):

- **identification** – related to the identification of threats, vulnerabilities and other risk factors;
- **analysis** – related to the assessment of these factors;
- **evaluation** – related to the consideration of the assessed risks and determination of priorities of intervention.

8. The EU SNRA, for example, explains that "the 'impact/consequences component is regarded as constantly significant and will therefore not be assessed. […]. While it is important to understand the consequences associated with the ML/TF activities (physical, social, environmental, economic and structural consequences), from a methodological point of view it is particularly challenging to measure their consequences in quantifiable or numerical terms. For the purpose of this risk assessment it is therefore assumed that ML/TF activities generate constant significant negative effects […]. From a methodological point of view, as the impact/consequences component is assumed as a fix high value […], the determination of the residual risk for each scenario (modus operandi versus scenario) will be determined by the combination of the identified level of threat and vulnerability only" (European Commission, 2015).

9. In other words, what is performed is an assessment of the ML likelihood and not properly of ML risk. But the expression "risk assessment" is kept for the sake of clarity and in line with current mainstream RA taxonomy.

IARM 7 steps

RISK FACTORS IDENTIFICATION

In each country, at each level (regional /or business sector), **ML risk factors are identified** through a review of the literature (academic papers, LEA/FIU/ARO reports, judicial evidence, other institutional reports) and are then validated through interviews with experts.

RISK FACTORS OPERATIONALISATION

For each risk factor identified, a range of **proxy variables** is identified and measured. Proxies might differ from country to country depending on the country-specific context and data availability.

DATA COLLECTION AND NORMALISATION

After factors and relevant proxies are identified, **data are collected** from a variety of sources (see chapters 2-4 and Annex for details), organised and validated. When necessary, data are treated through imputation of missing values, normalisation and transformation techniques.

DATA EXPLORATION AND CORRELATION ANALYSIS

Descriptive statistics and correlation analysis are produced among the identified variables, e.g. to see how variables distribute, relate and covariate and in order to identify outliers. The IARM approach keeps outliers in the model, because the exact aim is to identify those areas/sectors characterised by the highest risks.[10]

PRINCIPAL COMPONENT ANALYSIS

Variables are aggregated using **principal component analysis**[11] **(henceforth PCA)**, which makes it possible to identify (and determine the relative weight of) the different dimensions (components) of ML risk. Other aggregation and clustering techniques (e.g. factor analysis) are also explored to validate PCA results.

AGGREGATION AND COMPOSITE INDICATOR CONSTRUCTION

For each component extracted from the PCA, values are generated per each province and sector. The components are then **aggregated and combined into a composite indicator** of ML risk after appropriate weighting and normalisation. As a result, each province and sector is attributed a relevant value of the ML risk composite indicator ranging from 0 to 100.

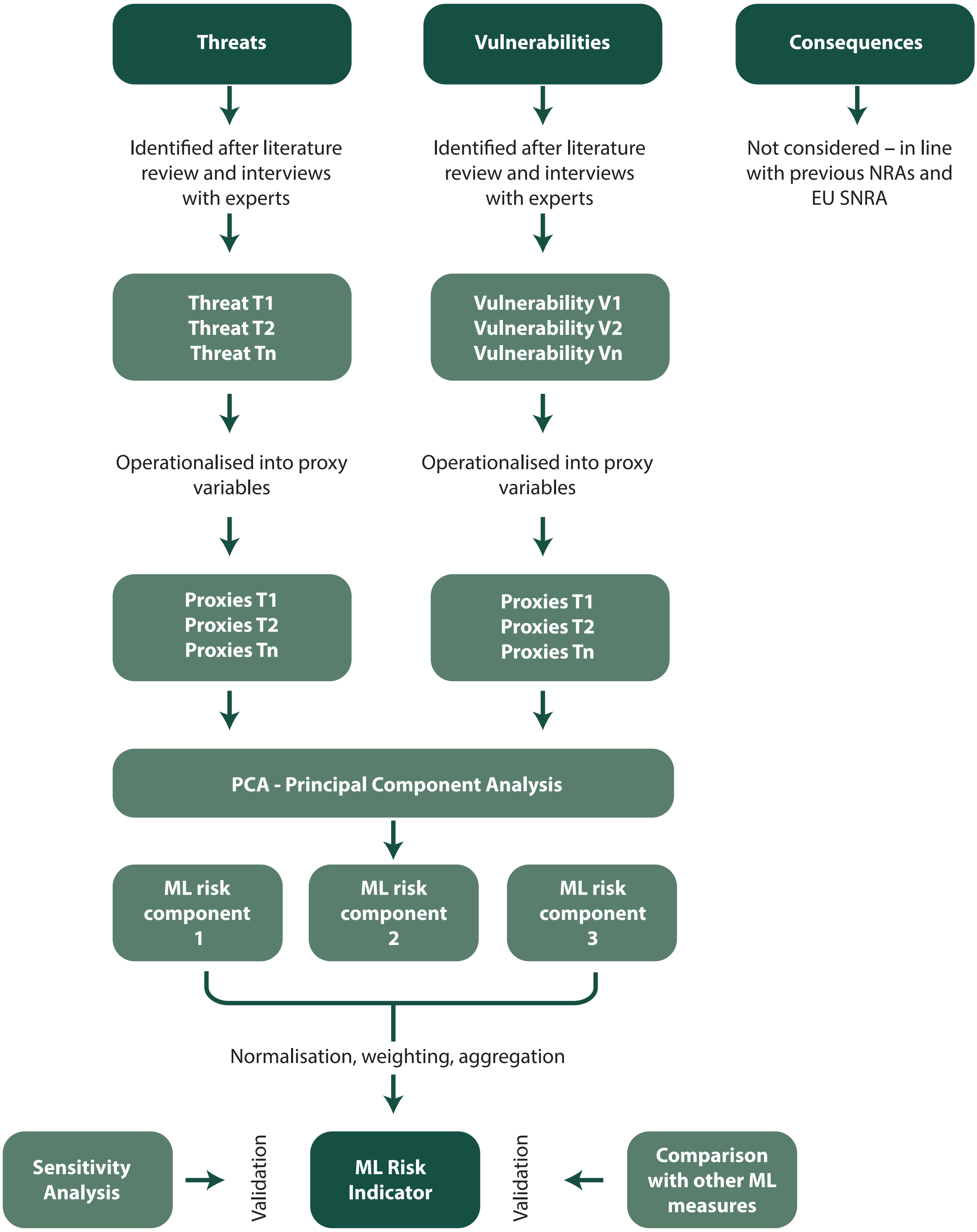
SENSITIVITY ANALYSIS AND VALIDATION

The composite indicator is validated in two ways. First, a **sensitivity analysis** is performed in order to determine whether and how it changes after modifying certain parameters in the process (e.g. normalisation and weighting criteria, type of PCA rotation, etc.) and after excluding certain variables from the model. Second, the indicator, where possible, is compared to alternative measures of ML (e.g. number of suspicious transaction reports – STRs) to see the extent to which they correlate.

10. The sensitivity analysis (STEP 7) proves that the approach is robust and results of the assessment is not driven by outliers.

11. Principal component analysis is a multivariate data analysis technique used, in a similar way to other approaches (e.g. factor analysis), to reduce the information contained in large datasets into a smaller number of components (or factors, in factor analysis), each of them able to summarise a specific phenomenon explained by a range of correlated variables. For this purpose, PCA uses an orthogonal transformation of the correlated variables into a set of principal components which are uncorrelated with each other (OECD & JRC, 2008; Jolliffe, 2002).

Figure 3 – From risk factors to a composite indicator of ML risk



Strengths and weaknesses

Strenghts

The IARM approach **complements existing ML/TF risk assessments** at national and supranational level, addressing some of the gaps of current approaches described in section 1.1. It builds on the FATF guidance, but stresses the quantitative method and incorporates some innovative elements, which are discussed below.

Higher disaggregation detail

IARM adopts a sub-national perspective (across the **Italian 110 provinces** and **UK 43 police areas**) while existing works have a national perspective. It also covers **all business sectors** (at the NACE division disaggregation, in Italy and the Netherlands) while existing studies focus only on regulated sectors (i.e. industries under AML obligations such as banks or professionals).

A synthetic measure of a complex phenomenon

IARM develops two **composite indicators** (at area and industry level) which **condense a complex and multifaceted concept like ML risk into one value**. Most existing NRAs adopt a qualitative approach, which yields an in-depth understanding of threats and vulnerabilities but lacks a bird's-eye perspective on the problem.

A transparent and replicable methodology

IARM adopts a **transparent methodology**, which is applied uniformly in the three countries covered by the study (Italy, the Netherlands, United Kingdom) and can be replicated also in other contexts and areas. Most other ML indicators do not disclose methodological details, which makes it difficult to cross-check, compare and validate results across areas, sectors and stakeholders.

An easy-to-use tool for practitioners

The indicator of ML risk produced by IARM can be easily **applied in the everyday work of practitioners** in the AML field: both investigators, who can improve the detection of risky areas, and obliged entities (e.g. banks, professionals, real estate agencies, high value dealers, etc.), which can use IARM ML risk indicators to improve the assessment of clients in their **customer due diligence (CDD)** activity.

An innovative analysis of the ownership structure of European businesses

Based on the analysis of a large volume of company data (provided by BvD), IARM has performed the first **large-scale investigation of who are the owners** of companies in Italy, the Netherlands and United Kingdom, and where they come from (see chapters 2-4 and in particular chapter 5). This analysis is particularly important in light of the recent developments in the EU AML regulatory framework, most notably the adoption of beneficial owner registries.

Weaknesses

Despite its innovative contribution, the approach adopted by IARM has some weaknesses and shortcomings:

- **only those RFs which can be actually measured given available data are covered.** For some serious ML threats and vulnerabilities (including important predicate offences like, e.g., **corruption and extortion)** reliable measures at sub-national and business sector level are not available, and for this reason they are not taken into account by the indicator;
- this means that the methodology does not fully take into account **emerging threats and vulnerabilities** which, by definition, are characterised by lack of data and estimates: for example, the use of virtual currencies or new payment methods (e.g. prepaid cards, mobile or internet based payments);
- given the **cross-regional** and **cross-sectorial focus**, the risk factors at the national level, such as the vulnerabilities in the AML regulation or in company law, are not taken into account in the IARM model, so that risk should not be compared among countries;
- like other risk assessment exercises (such as the EU SNRA or the Italian and British NRA), the indicator does not cover **ML consequences**: the risk assessment which stems from this approach therefore does not take into account the impact of money laundering activities across regions and sectors.

Table 2 – Strengths and weaknesses of the IARM methodological approach

STRENGTHS	WEAKNESSES
• Complex phenomenon condensed into a single measure of risk • Sub-national perspective (vs. NRAs' national perspective) • All business sectors covered (vs. NRAs' coverage of regulated sectors only) • Transparent and replicable methodology • Easily applied in the everyday work of AML practitioners (e.g. in CDD by obliged entities)	• Suffers from lack of data on certain risk factors (e.g. corruption) and emerging trends (e.g. virtual currencies, NPMs) • No coverage of risk factors at national level (e.g. weaknesses in AML legislation) • No coverage of ML consequences • Focus on ML (and not on TF)

Source: Authors' elaboration

1.4 Focus: ML threats, vulnerabilities, consequences

Threats

As mentioned, ML threats are people or activities that produce illicit proceeds or that may need to launder money. In other words, they are related to **ML predicate offences**. The literature identifies a wide array of threats. For example FATF, while recommending to expand as most as possible the range of predicate offences (FATF Recommendation 3[12]), suggests a list of **24 threat categories** to be considered in risk assessment (for a comprehensive review see FATF, 2013a, pp. 33–38). Among them:

- participation in organised crime
- human trafficking/smuggling
- illicit trafficking in narcotic drugs
- corruption and bribery
- tax and excise evasion

IARM focuses on those threats which are **particularly relevant (in terms of seriousness/volume of illicit proceeds generated)** in Italy, the Netherlands, and the UK, and **which can be measured** according to available data – with some differences among the three countries and if the analysis is conducted at territory or business sector level. They are illustrated in the following chart and discussed below.

Table 3 - Threats analysed by IARM by country

	Italy Regional analysis	**Italy** Business sector analysis	**The Netherlands** Business sector analysis	**UK** Regional analysis
Organised crime	●	●	●	●
Illicit markets	●	NA	NA	●
Drug trafficking	●	NA	NA	●
Sexual exploitation	●	NA	NA	+
ITTP	●	NA	NA	+
Counterfeiting	●	NA	NA	+
Property crime	+	NA	NA	●
Tax evasion (and underground economy)	●	●	●	+

● considered   NA not applicable   + not considered

Source: Authors' elaboration

12. "Countries should apply the crime of money laundering to all serious offences, with a view to including the widest range of predicate offences" (FATF, 2012, p. 14)

Organised crime

Organised crime (henceforth OC) involves a **wide variety of criminal activities**, many of which may be identified as predicate offences in their own right (e.g. illicit drug trafficking, extortion, etc.) and are discussed separately below. However, IARM assumes that OC can be considered as a threat alone itself. High levels of OC may in fact increase the likelihood of **criminal infiltration of the legitimate economy**, whatever the amount of proceeds generated by illicit markets, which in turn could increase the ML risk (Savona, Riccardi, & Berlusconi, 2016 - see Annex A1 for details).

Illicit drug trafficking

Historically, drug trafficking has been considered the **most serious money laundering predicate crime**. The modern AML regime was developed in the 1980s in order to fight the trafficking of narcotics, and FATF itself was conceived in the framework of the 1988 UN Convention against illicit traffic in narcotic drugs. According to recent estimates, the illicit retail drug market in Europe (heroin, cocaine, cannabis, amphetamines and ecstasy) amounts to between **20 and 30 billion euros per year**, equivalent to 0.2%-0.6% of EU GDP (EMCDDA, 2016; Savona & Riccardi, 2015).[13] How much of this figure is laundered, and where, varies. It depends on the market structure, the type of criminal group involved, and emerging trends – like the growth of home-made drugs (e.g. cannabis) or the availability of dark web drug markets (see Annex A1).

Other illicit markets

The coverage of other criminal offences and illicit markets considered in the IARM model depends on the availability of data: in Italy, estimates of illicit revenues at regional level (NUTS 2 disaggregation) are available for **sexual exploitation**, **illicit trafficking in tobacco products,** and **counterfeiting** (see Chapter 2). In the UK, good data at police area level are available for both drug trafficking and **organised property crime** (see Chapter 4). In the Netherlands, analysis is conducted only at business sector level, so that the concept of illicit markets does not apply. Unfortunately, no data are available at regional level on important predicate crimes – at least in the IARM countries – like **extortion racketeering** and **usury** (see Chapter 2). The same applies to **fraud** (e.g. MTIC fraud, excise fraud, credit card fraud, etc.) for which some estimates exist but only at national aggregate level.

Corruption

Corruption is related to ML as both a **predicate offence** (bribes and monetary benefits which are laundered in the legal economy) and a **facilitator** (e.g. corruption of a bank official in order to ease the deposit or transfer of illicit funds). Unfortunately, no data on the amount of corruption proceeds at regional level are available either in Italy or in the UK. At business sector level the concept of corruption threat is hard to operationalise and therefore is not taken into account. In Italy, given the close relationship between corruption (especially in public procurement) and organised crime, the phenomenon is indirectly measured by considering the level of OC presence and infiltration in the legal economy (see Chapter 2).

Tax evasion (and underground economy)

Tax evasion is an important **ML threat**. It is included in the predicate offences listed in the 4th EU AML Directive. However, it is also a good proxy for the underground economy which, in turn, is widely considered as a **vulnerability** in the ML risk assessment framework. The amount of illicit proceeds generated by tax evasion is huge, in all its forms: e.g. VAT and excise fraud, evasion of personal income taxes and of corporate taxes, evasion of local government taxes and social contributions. It is taken into account in the IARM model by using different proxies: tax gap in the analysis across Italian regions, labour tax irregularity in Italy at business sector level and corporate tax fraud in the Netherlands at business sector level – see respectively Chapter 2 and 4 for details.

13. In particular, EMCDDA estimates the illicit retail drug market in 2013 at between 20.8 and 30.8 billion euros (EMCDDA, 2016, p. 4). Transcrime's OCP project estimates that the drug market in the EU (on 2013-2015 data, depending on the drug) produces 27.7 billion euros per year at the retail level, equivalent to nearly 0.25% of EU GDP (Savona & Riccardi, 2016, p. 36).

Issues in measuring ML threats

Measuring ML threats means measuring the level or volume of people and activities, in a certain area or sector, that need to launder money. In other words, it means **assessing the scale of ML predicate offences in that area or sector** (FATF, 2013a, p. 7; Dawe, 2013, p. 112). There are three main critical issues in this assessment (see also Annex A1):

1. the choice of whether to **focus on people, activities or both**. For example it may be possible to assess the scale of the ML threat 'drug trafficking' in a certain area by measuring the number of recorded criminal groups (or criminals) involved in drug trafficking or by estimating the volume of illicit drug proceeds generated. It should not be assumed that both the approaches point in the same direction: for example, a certain area may have a low number of OC groups but a high volume of proceeds (e.g. because of a large consumer market). And much depends also on the chosen perspective, methodology and disaggregation level;[14]
2. the difficulties in **validating threat measures**. By definition, ML threats imply illicit transactions or hidden activities which are not recorded. In recent years, a number of studies have addressed the issue of how to estimate the scale of illicit markets, and estimation methodologies have much improved – although the risk of producing "mythical numbers" (Calderoni, 2014b, p. 138; Reuter, 1984, p. 135) still remains. Annex A1 provides a comprehensive review of threats measurement methodologies, showing how much they vary: for example, some may adopt a supply-driven or demand-oriented approach. Problems may arise if, e.g., threats measured with different approaches are then combined together;
3. The difficulties in taking the **transnational nature of ML threats** into account. Proceeds generated by the sale of drugs in a region or country *i* may be then laundered in another region or country *j*. Is the ML risk higher in region *i* or *j*? The literature, when dealing with threat analysis, stresses the importance of distinguishing between dirty funds produced locally or internationally. In other words, also "illicit proceeds generated outside […] that are likely to enter the jurisdiction for laundering" should be taken into account (Dawe, 2013, p. 112; FATF, 2013a). However, in practice, it is often almost impossible to follow this advice.

How IARM addresses these issues

In the IARM methodological approach, it is not possible, given the current availability of data, to use the same measurement method for each different threat. For example, while in some cases the focus is on *people* (e.g. number of OC groups per area *j*, as a proxy for organised crime across UK territories, see Chapter 4), in other cases it is on *activities* (e.g. estimated illicit revenues from drug trafficking or sexual exploitation, as proxies for these illicit markets in Italy). In doing so, IARM follows the most updated measurement methodologies as regards both illicit markets and organised crime (see Annex A1 and infra chapters).

As regards the transnational nature of ML threats, IARM is based on one assumption: that **illicit proceeds generated in an area (or sector) are laundered in the same area (or sector)**. In other words, it is not foreseen that one area may launder proceeds generated elsewhere. This is a major weakness of this approach – but it is the only one which could be adopted given the available knowledge and data on transnational (and trans regional) illicit flows.

However, to address this problem, it is assumed that the inclusion of ***vulnerabilities* in the model** (see below) could help in measuring the **'attractiveness' of a certain area (or sector) for dirty proceeds generated elsewhere:** e.g. if one area has relatively small illicit markets, but a high cash intensiveness which could ease the placement of illicit cash, then it may attract 'foreign' illicit funds. As a result, it may record low levels of ML threats but high ML vulnerabilities and then, overall, a medium-high ML risk.

14. The distinction between activities and structures is, for example, a central issue in the organised crime literature (see e.g. Riccardi & Berlusconi, 2016; von Lampe, 2015; Finckenauer, 2005).

Vulnerabilities

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 list of ML vulnerabilities could be almost endless. In its RA guidelines, **FATF identifies more than 60 vulnerabilities** grouped into six categories (the so-called P-E-S-T-E-L approach, see FATF, 2013, p. 42):

- political factors (e.g. "stability of the government", "level of political commitment to AML", etc.)
- economic factors (e.g. the "opacity of the financial system", "prevalence of cash-based transactions", etc.)
- social factors (e.g. "social inclusiveness", "ethnic diversity", "significant population shifts", etc.)
- technological factors (e.g. "use of technology in money transfers", "new communication methods", etc.)
- environmental factors (e.g. "availability of water", "re-use of resources", etc.)
- legislative factors (e.g. "strengths and weaknesses in AML legislation", "adequacy of AML controls", "limited regulation of money value transfer systems", etc.)

Such a wide perspective risks extending the assessment to **any social or economic factor**, including those which exert only very indirect effects on the likelihood of ML, and overburdening the model with factors which are virtually impossible to operationalise and measure.

IARM focuses only on a **limited number of vulnerabilities**: those which – according to the literature and experts' interviews – are particularly relevant in the country, for which data are available at regional and business sector level and which apply to the defined unit of assessment. For example, **weaknesses in the AML legislation** are not taken into account because they refer only to a national level while there are usually no differences in the regulatory regime across regions and sectors in the same country.

Table 4 – Vulnerabilities analysed by IARM by country

	Italy Regional analysis	**Italy** Business sector analysis	**The Netherlands** Business sector analysis	**UK** Regional analysis
Cash-intensiveness	●	●	●	●
Opacity of business ownership	●	●	●	●
High volume of money remittances	●	NA	NA	
Presence of transit hubs	●	NA	NA	●
Attractiveness of real estate market		NA	NA	●
Business profitability		●	●	

● considered   NA not applicable   + not considered

Source: Authors' elaboration

Cash-intensiveness

Cash-based economies and sectors are more vulnerable to money laundering. **Cash is a facilitator** for committing crimes (first of all tax evasion) and for concealing and laundering the proceeds of crime. It is **anonymous and cannot normally be traced**. It is a bearer negotiable instrument which gives no details either on the origin of the proceeds or on the beneficiary of the exchange (Soudijn & Reuter, 2016). This makes it harder for law enforcement to follow the audit trail (Riccardi & Levi, 2017; Europol, 2015). It is not surprising that most STRs/SARs around Europe are related to anomalous use of cash, and that most confiscated assets are in the form of cash or are movable goods.

In the framework of the IARM model, cash-intensiveness is analysed by considering two aspects:

- the extent to which cash is used as means of payment in a certain area;
- the cash-intensive nature of businesses in a certain area or sector.

The first is measured through an indirect proxy called **cash-ratio**, available at regional level only in Italy (see Chapter 2). The latter is analysed in all the three IARM countries (at both territorial and/or business sector level) by measuring the average value of companies' **cash (and other current assets) on the total assets** in a certain area or sector (see Annex).

Opacity of business ownership

Complex corporate structures, especially if established in risky jurisdictions with a low level of financial transparency, are helpful for **concealing illicit flows and hiding beneficial ownership** (FATF, 2016b, 2014a; Reuter, 2012; de Willebois, Halter, Harrison, Park, & Sharman, 2011; Blum, Levi, Naylor, & Williams, 1999). The need for more precise and **transparent information on business ownership** (in particular on beneficial owners – henceforth BO) has been stressed by FATF Recommendations and then acknowledged at EU level in the latest AML Directive. However, problems of accessing data on ownership across different business registers and jurisdictions remain (Riccardi & Savona, 2013; EBOCS Consortium, 2015).

For all these reasons, the opacity of business ownership is a **key ML vulnerability**. In the IARM context, it is analysed by considering two sub-dimensions:

- the **level of complexity** of businesses' ownership structure as such;
- the volume of business ownership connections with shareholders and BOs from **risky jurisdictions**.

They are measured by means of **innovative proxies** applied to an invaluable set of data on business ownership provided by **Bureau van Dijk (BvD)**. Opacity of business ownership is analysed in Italy (Chapter 2), the Netherlands (Chapter 3) and the UK (Chapter 4) at both territorial and business sector level. Chapter 5 provides a comparative overview across the three countries.

Other vulnerabilities at territorial level

When carrying out the risk assessment at regional level in Italy and the UK, other ML vulnerabilities are considered. In both the countries, the **presence of transit hubs** (e.g. international airports, ports, intermodal freight stations) is considered to increase the risk of illicit financial flows, for example of cash-smuggling (FATF, 2015b; Soudijn & Reuter, 2016).

In Italy, the literature stresses the role of **money transfer services** in facilitating illicit financial flows: for example, the movement of proceeds produced by Chinese-speaking criminal organisations and other foreign OCGs (Clemente, 2016; Maresca, 2016; CSF, 2014a, p. 23). Therefore, a measure of the volume of money remittances per capita is included in the model (see Chapter 2).

In the United Kingdom, the **real estate market** is widely considered to be an attractiveness factor for both legal and illicit financial flows (HM Treasury, 2015; Goodrich & Cowdock, 2016). For this reason, a proxy for the relative increase in property values across UK areas is included in the analysis as ML vulnerability (see Chapter 4).

Other vulnerabilities at business sector level

There is no general agreement on whether the **profitability of a business sector** should be considered a money laundering vulnerability: some scholars argue that profitable businesses may attract illicit investments (Kruisbergen, Kleemans, & Kouwenberg, 2015; Masciandaro, Takæts, & Unger, 2007, p. 7; Unger & Rawlings, 2008; Williams, 2001). But, despite some single case studies (e.g. renewable energy in Italy or VLT/gaming in some EU countries) the empirical evidence showing a correlation between money laundering/criminal infiltration and industry's profitability is weak (e.g. see Riccardi, 2014; Donato, et al. 2013; Transcrime, 2013). For this reason, in the IARM analysis at business sector level in Italy and in the Netherlands, **two models** are presented: one including profitability as a ML vulnerability, and one excluding it (see Chapters 2 and 4).

Issues in measuring ML vulnerabilities

There are various challenges in measuring ML vulnerabilities: first, **the lack of appropriate proxies** to operationalise complex and multifaceted phenomena (such as cash-intensiveness, opacity of business ownership, and others); second, the **paucity of data** related to some of these factors. The difficulties increase when the analysis is carried out at business sector level, where data are scant and the relevant literature is still in its infancy.

How IARM addresses these issues

IARM develops an innovative set of proxies and indicators for ML vulnerabilities. Some – e.g. the measures of cash intensiveness or of business profitability – are operationalised by taking inspiration from the literature in other domains (e.g. accounting, corporate finance, monetary economics, corporate governance, etc.). Others – e.g. the measures related to the complexity of business ownership structure, to the degree of connections with risky jurisdictions, etc. – are very new proxies which for the first time are applied at a regional or sectorial level (while normally they are used at a *micro* level, i.e. for the analysis of individual firms).

Consequences

The FATF RA guidance defines ML/TF consequences as "the impact or harm that ML or TF may cause and includes the effect of the underlying criminal and terrorist activity on financial systems and institutions, as well as the economy and society more generally" (FATF, 2013a, p. 7). This means that the effect of money laundering includes all the **consequences of all different predicate crimes**, making it a very broad subject.

Moreover, as mentioned, FATF admits that measuring consequences may be very difficult, and it suggests focusing only on assessment of threats and vulnerabilities. The majority of available NRAs (and the EU SNRA itself) adopt this approach and exclude analysis of consequences from ML risk assessment.

IARM does likewise and **focuses only on threats and vulnerabilities.** However, the following paragraphs provide a brief overview of the consequences of money laundering with a specific focus on the empirical underpinning. An in-depth literature review is provided in the Annex.

ML consequences may be **positive or negative**, of an **economic and non-economic nature.** They may have an effect on the **real sector, on the financial one**, or on the public and monetary market. They may be appreciated in the **short or long term**. But most of them are **not supported by empirical evidence**. Empirical studies on ML impact are hampered by the lack of a reliable estimate of the amount of money laundering across countries and over time (Levi & Reuter, 2006, p. 294). Unger et al. (2006, p. 102) conclude that "most literature on money laundering effects is pure speculation [..] one source refers to the other source, without much of an empirical solid back up".

Table 5 below reports a list of **24 categories of consequences** (focusing only on those generated by ML itself, and not by predicate offences) stemming from a comprehensive literature review based on Ferwerda (2013) and Unger (2007; 2006).

Table 5 – The consequences of money laundering as mentioned in the literature[15]

	Economic	Non-economic	Effect in which Sector?			Short term	Long term
			Real	Financial	Public and monetary		
1. Law enforcement gets a second chance		•	•			•	
2. Distortion of consumption	•		•			•	
3. Distortion of investment and savings	•		•				•
4. Artificial increase in prices	•		•			•	
5. Unfair competition	•		•			•	
6. Changes in imports and exports	•		•			•	
7. Decrease of economic growth	•		•				•
8. Decrease of output income and employment	•		•			•	
9. Higher/lower revenues for the public sector	•				•	•	
10. Threat to privatisation	•	•			•		•
11. Changes in the demand for money, interest and exchange rates	•				•	•	
12. Increase in the volatility of interest and exchange rates	•				•	•	
13. Changes to availability of credit	•		•			•	
14. Higher capital inflows/outflows	•			•	•	•	
15. Changes in foreign direct investment	•		•		•		•
16. Risk for the financial sector, solvability and liquidity	•	•		•			•
17. Profits for the financial sector	•			•			•
18. Reputation of the financial sector		•	•	•			•
19. Contamination of illegal business by legal business	•	•	•	•			•
20. Distortion of economic statistics		•			•	•	
21. Corruption and bribery		•	•	•			•
22. Increase in crime		•	•		•		•
23. Undermining of political institutions		•			•		•
24. Undermining of foreign policy goals		•			•		•
25. Increase in terrorism		•			•		•

Source: Authors' elaboration

15. See the Annex for the sources of each category of consequence. Although this literature overview is based on an extensive literature search, its completeness can, of course, not be guaranteed. The review is based on a systematic reviewing of the publications by international organisations such as the International Monetary Fund (IMF), Organisation for Economic Development (OECD) and the Financial Action Task Force (FATF). In addition Econlit, an economic search database that includes about 750 journals and over 44,000 working papers, has been browsed. Other sources used are the Dutch Central Catalogue (NCC), which includes around 14 million books and 500 000 magazines and Google Scholar. Specific focus was given to the Journal of Money Laundering Control and the Journal of Financial Crime. This overview is an updated version of the one published in Unger et al. (2006, pp. 110–111), Unger (2007) and (Ferwerda, 2013).

Law enforcement gets a second chance

The first is somehow a positive effect. Criminalisation of money laundering gives law enforcement agencies a second chance to catch the criminal. Even if the police are unable to prove the original crime, the **criminal can still reveal himself** when he starts to transfer/transform/invest the money made from his crime. And he can still be convicted for money laundering, and the proceeds of the crime can be confiscated (Ferwerda, 2012).[16] This consequence is not really a risk factor for a risk assessment, since it is the result of considering money laundering a crime, not an effect that happens when money laundering is committed. However, this effect is included to keep the literature overview complete.

Distortion of consumption, investment, savings, imports and exports, output, income and employment

The criminalisation of money laundering may make **criminals spend their money differently** (Walker, 1995; 2016). Criminals may buy or invest solely for money laundering purposes (for instance in real estate). They may not buy something because it might attract the attention of the authorities, or select suppliers in order to avoid the suspicion of money laundering. Criminal organisations usually opt for laundering in cash-intensive assets or business sectors (such as bars, restaurants, gambling/betting activities) which facilitate the placement of illicit proceeds (Riccardi & Levi, 2017; Kruisbergen et al., 2015; Transcrime, 2013). This may result in **financial resources allocation in sub-optimal industries** and distort markets – especially if businesses used by criminals to launder adopt illicit behaviours such as extortion, corruption, accounting manipulation or market abuse. When the different spending and investing pattern is related to foreign-produced goods, it also has an effect on imports and exports. This consequence seems to be particularly important for developing countries, where rich criminals spend their money on imported luxury goods rather than on local products (Bartlett, 2002, p. 20).

16. This idea seems to be the reason that money laundering was criminalized in the first place. When the US found that it could not win the 'war on drugs', it decided to go after the money made from the drugs trade. In 1986, the Money Laundering Control Act was enacted, which basically started a 'war on drugs money' (Ferwerda, 2012).

However, **empirical evidence in this regard is poor**, apart from some countries. In **Italy** a variety of studies show that mafia investments in legal businesses differ substantially from legal investments (Riccardi, Soriani, & Giampietri, 2016; Riccardi, 2014; Transcrime, 2013) and that the impact on market, investments and import/export is substantial (Pinotti, 2015; Gurciullo, 2014; Lavezzi, 2008). In the **Netherlands**, empirical evidence shows that the spending behaviour of criminals is not substantially different from that of normal people (Unger, 2007, p. 122) compares Meloen et al. (2003) with Alessie et al. (2002, p. 358), so that the distortion may not be that large.

Artificial increase in prices and unfair competition

Related to the previous category of consequences is the possible impact of investments of criminal proceeds in terms of artificial increases in prices. Because of their large funds, criminals will for example **outbid honest buyers** to acquire assets (Walker, 1995, p. 33). Or they may be able to make very low (and unfair) tenders in response to **public and private procurement announcements**, outbidding legal competitors (Fazekas, Sberna, & Vannucci, 2016). In regard to the first consequence, there is some anecdotal evidence concerning the effect on land prices in Colombia of the laundering of proceeds by the Medellin Cartel (Keh, 1996, p. 5); in regard to the second, there is a large body of literature (Fazekas et al., 2016; PWC & Ecorys, 2013; Chaikin & Sharman, 2009; Baker, 2005).

Capital outflows and effects on volatility of exchange and interest rates

Some scholars point out the effects produced by illicit inflows/outflows in terms of volatility of exchange and interest rates which **directly affect the demand for money** (Tanzi, 1997, p. 8; McDonell, 1998, p. 10; Camdessus, 1998, p. 2; FATF, 2002, p. 3; Boorman & Ingves, 2001, p. 9). In particular, considering the capacity of Western economies to attract illicit financial flows from the rest of the world, various scholars stress the harm caused by global ML to developing countries – which are impoverished by cash outflows (Hendriyetty & Grewal, 2017; Kar & Spanjers, 2015; Bartlett, 2002).

Reputational damages

The literature identifies two main concerns regarding the financial sector. First, if launderers' economic behaviour is less predictable than that of conventional investors, there may be some risk **for the solvency and liquidity of the financial sector** (Alldridge, 2002, p. 310). The second effect involves reputation: when money laundering operations are detected, the financial sector – specifically the financial institutions concerned – **will lose credibility and customer confidence** (Bartlett, 2002). This applies also at country level: a negative reputation for countries could produce a detrimental effect on inward foreign direct investments (Boorman & Ingves, 2001, p. 9).

Greater availability of credit in the short run, shortage in the long run

Related to the previous point, financial institutions may benefit from higher deposits and inflows of dirty money. This may lead to a **greater availability of credit**, even for legitimate businesses (Unger, 2007, p. 140). This is not, per se, a negative effect, at least in the short term, but **in the long run it may produce market distortions**, e.g. on how this credit is allocated. Moreover, if illicit funds are frozen or seized, it could turn in shortage of credit producing as mentioned solvency and liquidity risks.

Increases in crime

Money laundering may increase crime. It makes criminal activities worthwhile and provides criminal organisations with capital that they can use to **expand their criminal activities** (Mackrell, 1997). If governments succeed in making money laundering difficult, becoming a criminal will be less attractive[17] since it will be harder to enjoy the illicit gains – even when the crimes committed result in large gains and are not detected. A study by Ferwerda (2009) suggests that anti-money laundering policy can be used to reduce crime levels, and that more intense international cooperation in the fight against money laundering could be associated with lower crime rates.

Detrimental effects on economic growth

Money laundering can **dampen economic growth** because of the negative implications in terms of market distortions and misallocation of funds (Tanzi, 1997, p. 96; Bartlett, 2002, p. 18). Quirk (1997) and Ferwerda & Bosma (2005) provide evidence in this regard. Ferwerda & Bosma (2005) point out that crimes that are intermingled with money laundering actually hurt the economy more than money laundering itself.

17. How AML policy influences the incentives of (potential) criminals is modeled in Ferwerda (2009). One can use this model to show algebraically that anti-money laundering policy reduces crime.

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2. Italy

This chapter presents an analysis of the main risk factors of money laundering in Italy, across the 110 Italian provinces and at business sector level (across 77 NACE divisions).

It is structured as follows: first, it provides background on ML risk assessment in Italy (Section 2.1). Second, it presents the analysis at sub-national area level (Section 2.2). It then presents the analysis at business sector level (Section 2.3). Finally, it discusses some research and policy implications (Section 2.4).

Main findings - Italy

- IARM carried out an exploratory assessment of ML risk in Italy. In particular, it developed a composite indicator:
  - at territory level, across the country's 110 provinces
  - at business sector level, across 77 NACE divisions
- the analysis provides empirical support for (and complements) the 2014 National Risk Assessment (NRA). Moreover, it confirms some of the main findings of the 2016 FATF Mutual Evaluation Report (MER) of Italy.

Assessment at territory level: ML risk across the 110 Italian provinces

- At territory level (110 provinces), IARM identified and analysed 6 risk factors of money laundering:

  1. Organised crime infiltration
  2. Illicit markets
  3. Tax evasion & Underground economy
  4. Cash-intensiveness
  5. Opacity of business ownership
  6. Money transfers

- The six risk factors are operationalised in proxy variables and then combined, through principal component analysis (PCA), in a composite indicator of ML risk;
- According to the composite indicator, the provinces with the highest ML risk are in the south, with four Calabrian provinces at the top (Reggio Calabria, Vibo Valentia, Catanzaro, Crotone) followed by other southern areas (e.g. Naples, Caserta, Palermo, Trapani);
- These provinces record high levels of mafia-type infiltration, cash-intensiveness and underground economy (measured by tax gap and irregular labour);
- Among non-southern regions, Imperia and Prato rank highest. They record high levels of opacity of business ownership, cash-intensiveness, underground economy and (in the case of Prato) money remittances;
- The ML risk composite indicator at province level is significantly correlated with the rate of STRs – although some provinces seem to "under-report" with respect to their estimated level of risk.

Assessment at business sector level: ML risk across 77 NACE divisions

- At business sector level (77 NACE divisions) the analysis is more difficult – due to lack of available data and of appropriate proxies. Therefore, only and exploratory assessment is completed.
- IARM has identified 4 risk factors of money laundering:

  1. Organised crime infiltration
  2. Underground economy
  3. Cash-intensiveness
  4. Opacity of business ownership

Another model is developed including a further risk factor, business profitability (the more profitable, the more vulnerable to ML).

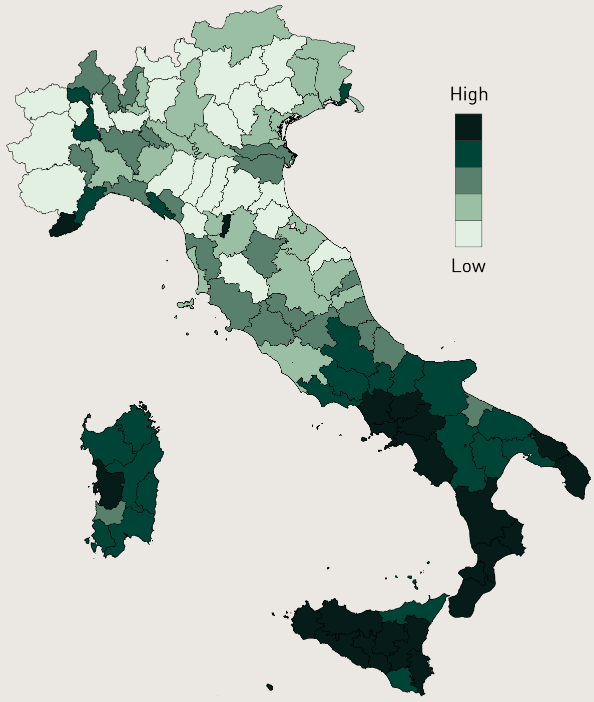
- As in the territory analysis, risk factors are combined in a composite indicator of ML risk
- According to the model, the economic sector in Italy with the highest ML risk are bars and restaurants (NACE division I 56): it is a traditional cash-intensive activity, but it shows also high levels of opacity of business ownership, irregular labour and mafia-type infiltration
- Divisions of NACE sector S come second. These include a variety of businesses, from repair services, to personal service activities - like massage parlours, beauty centres and spas - but also security and investigation companies and fiduciary services
- Ranking high are R 92 (Gambling and betting agencies) and R 93 (recreational activities ranging from VLT rooms to beach facilities – stabilimenti balneari): both divisions are characterized by relatively high evidence of mafia-type infiltration and high opacity of business ownership

- Sectors related to the building industry supply-chain also show high ML risk: mining (NACE section B), cement production (NACE divisions C 19 and C 23), construction (section F), landscaping, architectural and civil engineering professional businesses (divisions N 81, M 73 and M 71).

Research and policy implications

- The indicators produced by IARM respond to the need, stressed by regulatory developments at both EU and Italian level (see proposed changes to L. 231/2007, art. 15), to develop more objective and solid methodologies for ML risk assessment
- In particular they can be used by, for example:
  - Policy-makers, to support the design of more evidence-based and specific interventions
  - Investigators, to identify more easily anomalies and emerging ML trends (if the exercise is repeated over time)
  - Obliged entities (e.g. banks or professionals), to facilitate customer due diligence (CDD) and assessment of clients' risks
- However, IARM quantitative assessment should be combined with the qualitative approach adopted by NRA 2014 and FATF MER 2016 in order fully to appreciate ML risks in the country
- Future developments should improve data availability and quality, refine proxies for risk factors and explore alternative proxies and measurement approaches.

ML risk across 110 Italian provinces



Source: Transcrime - UCSC elaboration

ML risk – first 10 NACE divisions

	Business sector (NACE division)	ML COMPOSITE INDICATOR SCORE
	I 56. Food and beverage service activities	100.0
	S 95. Repair of computers and personal and household goods	80.4
	S 96. Other personal service activities	67.3
	N 79. Travel agency tour operator reservation service and related activities	64.4
	R 92. Gambling and betting activities	63.5
	R 90. Creative arts and entertainment activities	62.1
	P 85. Education	61.6
	A 03. Fishing and aquaculture	61.0
	M 74. Other professional scientific and technical activities	60.4
	C 19. Manufacture of coke and refined petroleum products	59.1

Source: Transcrime - UCSC elaboration

2.1 Introduction and background

In recent years, the understanding of money laundering risks in Italy (and of the effectiveness of AML countermeasures) has benefited greatly from two reports (see box below):

- The **National Risk Assessment (NRA)** published in December 2014 (CSF, 2014a);
- The **FATF mutual evaluation report (MER)** published in February 2016 as a result of the mutual evaluation process conducted in 2015-2016 (FATF, 2016a).

IARM builds on these two exercises. It complements the NRA and provides an added value by incorporating some innovative elements:

- It adopts a **sub-national disaggregation**, while the NRA has only used a national approach;
- It covers **all the economic sectors**, while the NRA does not adopt a sectorial perspective;
- It stresses the **quantitative approach**, ultimately producing a composite indicator of ML risk.

The combination of the findings of IARM, the NRA 2014 and the MER 2016 could contribute to more in-depth knowledge on how ML risks develop in the country and vary across areas and economic activities.

The Italian ML NRA 2014 and the MER 2016

The first **ML National Risk Assessment (NRA)** was carried out in 2014, in compliance with FATF Recommendation no. 1, by the **Financial Security Committee (*CSF - Comitato di Sicurezza Finanziaria*)**. It involved supervisory authorities, the FIU, LEAs, financial institutions, professionals, the national statistical office (ISTAT), the private sector and academics (CSF, 2014b, p. 2). The Italian NRA has encompassed:

- An assessment of the **inherent ML and TF risks** through identification of threats to and vulnerabilities of the socio-economic system;
- An assessment of the **effectiveness of the AML/CFT regime** at preventive, investigative and enforcement levels and focusing on the categories of entities subject to AML/CFT obligations (financial intermediaries, professionals, non-financial operators).

On the other side, The Fourth Round **FATF Mutual Evaluation Report (MER)** of Italy was published in February 2016 as a result of the **AML/CFT assessment conducted by the IMF** in 2015 (including on-site visits). The report, in line with the FATF approach, assesses a) the country's level of compliance with the 40 FATF Recommendations and b) the level of effectiveness of its AML/CFT system.

According to the MER, Italy faces **significant ML risks** but has a "**mature and sophisticated AML/CFT regime**, with a correspondingly well-developed legal and institutional framework" (FATF, 2016a, p. 19). In particular, as regards technical compliance, Italy is evaluated as compliant - see taxonomy in (FATF, 2013b, p. 5) - with 10 Recommendations; largely compliant with 26; partially compliant with 4 recommendations. No recommendations are rated as non-compliant (FATF, 2016a, p. 14). In terms of effectiveness, 11 aspects were rated from high to low, with the result of 8 aspects with substantial effectiveness and 3 with moderate effectiveness (see Methodological Annex).

Both the NRA and MER exercises stress that ML inherent risks in Italy are related to three main issues: **tax crimes**, serious and **organised crime** (with a key role of corruption) and the **cash-intensive nature** of the domestic economy (CSF, 2014a, p. 12; FATF, 2016a, p. 17). All these factors emerge clearly also from the IARM statistical analysis as major threats and vulnerabilities in the country.

2.2 Analysis at sub-national area level

The idea behind this chapter, as with the whole IARM approach, is that the overall **ML risk** of a given Italian province or business sector is a function of the level of the **ML risk factors** in that area or sector. The composite indicator of ML risk at province and business sector level is developed following the **7 methodological steps** described in Chapter 1. They are illustrated in detail below.

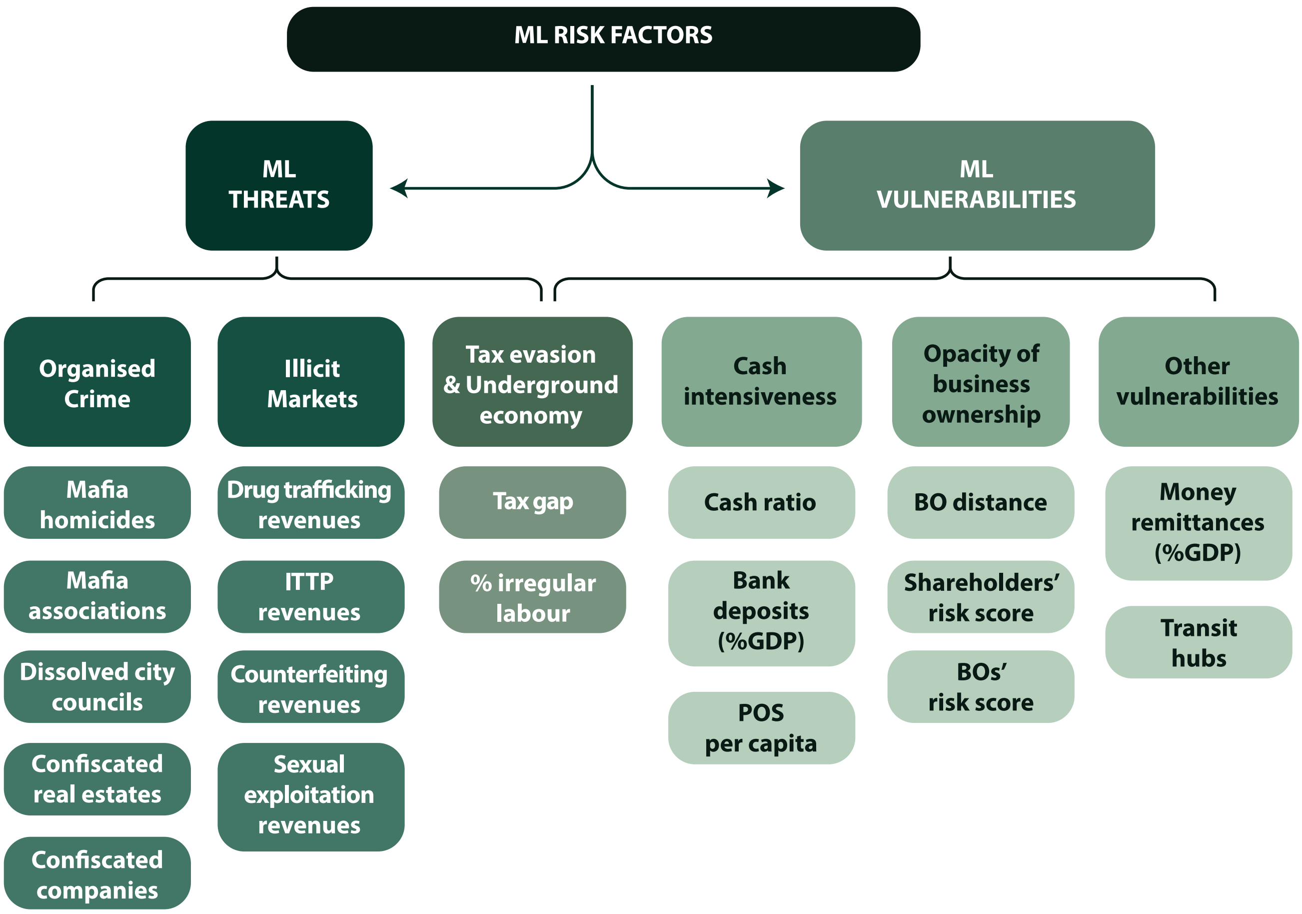
STEP 1 – ML RISK FACTORS IDENTIFICATION

ML risk factors (henceforth RF) across Italian regions are identified on the basis of a **review of academic literature, institutional reports, investigative and judicial evidence**, and then validated by means of interviews with experts. Although the starting list of RF suggested by FATF and the relevant literature (see (FATF, 2013a; Dawe, 2013), is very long, the analysis reported here focuses on those which:

- are particularly important in the Italian context;
- allow for in-depth analysis because of data availability.

Identified RF are classified according to the FATF taxonomy (*Threats, Vulnerabilities and Consequences* – see Chapter 1) and conceived in a **tree-structure** (*risk dimensions, risk factors, proxy variables*) which is depicted in the chart below. As mentioned, the focus is posed on **threats and vulnerabilities**, while consequences are not included in the analysis (see Chapter 1).

Figure 4– ML risk factors and proxy variables at sub-national area level in Italy



Source: Transcrime – UCSC elaboration

STEP 2 – ML RISK FACTORS OPERATIONALISATION

Each risk dimension, and in particular each risk factor, is *operationalised* into one or more **proxy variables** in order to allow for their measurement and analysis. Proxies have been identified according to previous literature and data availability, and are illustrated in the table below (see Annex for details).

Some phenomena which are stressed by the literature as important RF for money laundering in Italy – such as **corruption, usury, extortion** (see (CSF, 2014b; FATF, 2016a) – are not included in the model because of the lack of measures and estimates at sub-national level.[18]

Money laundering threats

Threats are identified starting from the **predicate offences** listed by the FATF (FATF, 2013a), reported in the 4th AMLD (Directive 2015/849, Art. 3) and by the CSF in the latest NRA (CSF, 2014a).

Table 6 - List of ML threat proxy variables at sub-national area level

ML Risk factor	ML Risk sub-dimension	Proxy variable	Variable labels	Source	Disaggregation level	Available years
Organised crime (OC)	OC presence	Mafia homicides / Population	*MAFIA_HOMICIDES*	Ministero dell'Interno / ISTAT	NUTS 3 (Province)	2009 - 2014
		Mafia associations (416bis) / Population	*MAFIA_ ASSOCIATION*	Ministero dell'Interno / ISTAT	NUTS 3 (Province)	2009 - 2014
	OC infiltration	Dissolved city councils / Population	*PA_DISSOLVED*	Ministero dell'Interno / ISTAT	NUTS 3 (Province)	2009 - 2014
		Seized companies / Registered companies	*SEIZED_ COMPANIES*	DIA	NUTS 3 (Province)	2013 - 2014
		Confiscated companies / Registered companies	*CONFISCATED_ COMPANIES*	ANBSC	NUTS 3 (Province)	2004 - 2012
		Confiscated real estate / Registered houses	*REAL_ESTATE*	ANBSC	NUTS 3 (Province)	2009 - 2012
Illicit markets	Drug trafficking	Illicit drugs revenues as % GDP	*DRUG*	Giommoni, 2014	NUTS 2 (Region)	2008, 2011, 2012
	ITTP	ITTP revenues as % GDP	*ITTP*	Calderoni, 2014	NUTS 2 (Region)	2006 - 2013
	Counterfeiting	Counterfeiting revenues as % GDP	*COUNTERFEITING*	Calderoni, Favarin, Garofalo, & Sarno, 2014	NUTS 2 (Region)	2008

18. For example, estimates of the illegal revenues produced by extortion exist at the national level (see (Lisciandra, 2014; Transcrime, 2013)) but not at regional level. The same applies to usury (see (Scaglione, 2014). Available measures at sub-national level, such as administrative or judicial statistics on people reported to the police, prosecuted or sentenced, are considered unreliable for these offences due to the high dark number and data variability. As regards corruption, no reliable measures exist at the regional level. The on-going victimisation survey conducted by ISTAT (ISTAT, 2016b) could in the future provide key indications of how this phenomenon varies across territories in the country. However, given that corruption in Italy is strictly related to infiltration in public procurement (Fazekas, Sberna, & Vannucci, 2016; Fondazione Res, 2014; Transcrime, 2013), it is partially covered in the model because of the inclusion of a wide variety of measures of organised crime and mafia infiltration in the legitimate economy and in the public administration.

ML Risk factor	ML Risk sub-dimension	Proxy variable	Variable labels	Source	Disag-gregation level	Available years
Illicit market	Sexual exploitation	Sexual exploitation as % GDP	*SEX_ EXPLOITATION*	Mancuso, 2014	NUTS 2 (Region)	2004 - 2009
	Other illicit markets	*No reliable estimates at sub-national area level*				
Corruption	*No reliable estimates at sub-national area level*					
Tax Evasion & Underground economy	Tax evasion	Tax gap (%)	*TAX_GAP*	Agenzia delle Entrate	NUTS 3 (Province)	2001-2009
	Irregular labour	Irregular labour (% of total labour units)	*IRREGULAR_ LABOUR*	ISTAT	NUTS 2 (Region)	2001-2010

Source: Transcrime – UCSC elaboration

Organised crime

Organised crime is widely recognized as one of the main ML RF in the country (FATF, 2016a, p. 6; CSF, 2014a; DIA, 2015; Visco, 2015). Although constantly evolving, it can be classified into two categories: indigenous OC groups, with a predominant role of **Italian mafias**, and foreign groups, in particular **Chinese-speaking and Eastern European OC** (Becucci & Carchedi, 2016; DIA, 2015; Ministero dell'Interno, 2014; Varese, 2001). Both play a major role in illicit markets; but, with some exceptions,[19] most evidence on ML activity is related to Italian mafias (DIA, 2015, 2014, DNA, 2014, 2013). It is therefore on the latter that the analysis is focused. In particular mafia-type OC is analysed with respect to two sub-dimensions: presence and infiltration in the legal economy.

Building on previous exercises (Calderoni, 2011; Transcrime, 2013; Fondazione Res, 2011; Asmundo, 2011), **mafia presence** is measured in terms of mafia homicides and attempted homicides (representing the violent component of mafias) and the number of people reported to the police because of mafia association (Art. 416-bis of the penal code). In both cases, southern provinces (especially in Calabria) show the highest levels.

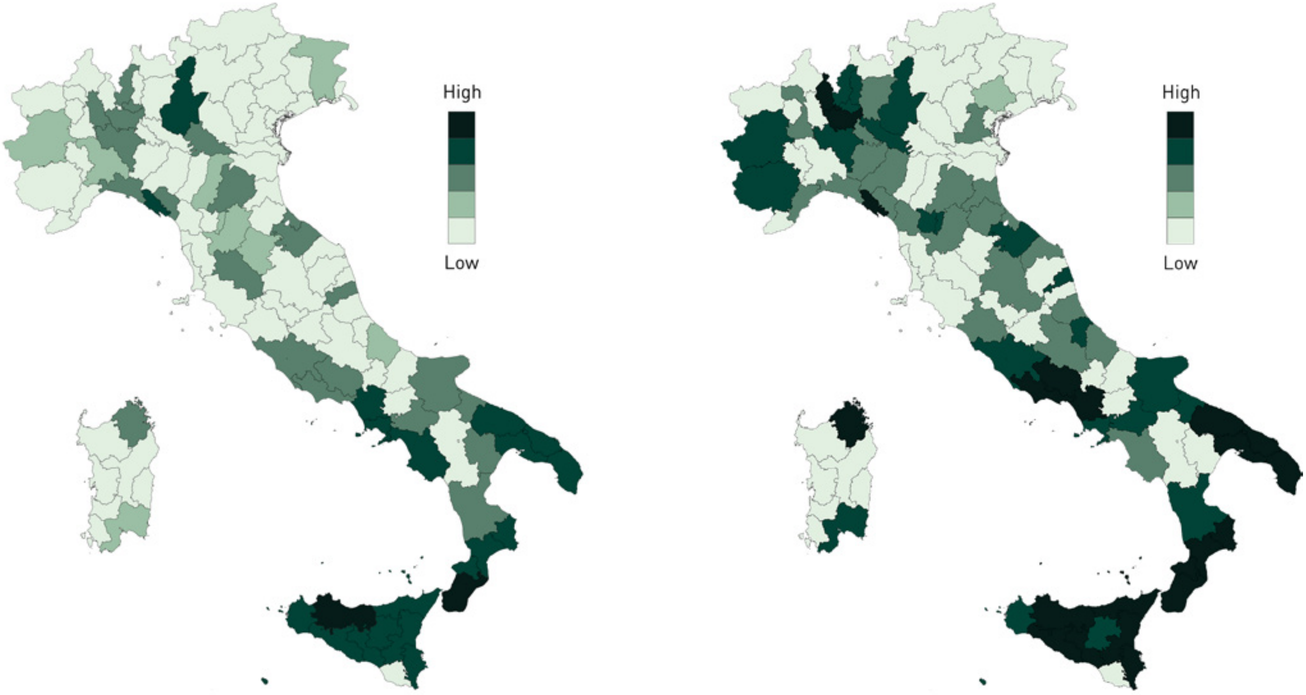
The **mafia infiltration** component is instead measured through three proxy variables:

- the number of city councils and public agencies dissolved due to mafia infiltration (Calderoni, 2011; Transcrime, 2013; Barone & Narciso, 2012; Coniglio, Celi, & Scagliusi, 2010), as a measure of infiltration in the **public administration**;
- the number of real estate assets confiscated from mafia groups, as a measure of investments in the **real estate sector** (Transcrime, 2013; Dugato, Giommoni, & Favarin, 2015);
- the number of confiscated companies as a measure of **infiltration in legitimate businesses** (Riccardi, Soriani, et al., 2016; Riccardi, 2014; Transcrime, 2013).

Also in this case ratios are higher in southern Italy, confirming a strict relationship between mafia presence and investment/infiltration (Riccardi, 2014; Transcrime, 2013; Pinotti, 2015). However, also some areas in the north (especially in Lombardy, Liguria, Piedmont and Emilia-Romagna) record high ratios. It is widely acknowledged, by both scholars and public officials, that **infiltration in non-traditional regions** has increased as a result of the transplantation of mafia groups following business opportunities, in particular large-scale public works (Riccardi, Soriani, et al., 2016; Balsamo, 2016; CROSS, 2015; Fondazione Res, 2014).

19. See e.g. the Qian Liu and Qian Ba operations against Chinese OCGs which revealed extensive ML schemes and illicit financial flows from Italy to abroad (Riccardi, Soriani, & Giampietri, 2016, p. 131).

Figure 5 - Confiscated companies (left) and confiscated real estate (right)
Ratio on registered companies (2004-2014) and registered houses (2009-2012).



Source: Transcrime – UCSC elaboration of ANBSC – DIA data

Illicit markets

The volume of illicit markets in Italy is significant and constitutes a major ML threat in the country (FATF, 2016a). As measures at sub-national level, **estimates of the illicit revenues generated by these markets at the retail level** are used, on the rationale that the higher the volume of illicit proceeds in a certain region, the higher the ML risk in that region.[20] Unfortunately it is not possible to use the recent estimates produced by ISTAT (ISTAT, 2016a) on three main illicit markets (drugs, illicit tobacco and prostitution) because they are only available at the national level. Therefore the **estimates produced by Transcrime** in 2013 (Transcrime, 2013; Calderoni, 2014a; Calderoni et al., 2014; Giommoni, 2014; Mancuso, 2014) on four illicit markets (illicit drugs – including cannabis, cocaine, heroin, synthetic drugs – ITTP, counterfeiting and sexual exploitation) are preferred. They are the one closest to official ISTAT figures,[21] they have a regional (NUTS 2) disaggregation level; and they adopt a common methodological approach (see Annex for details). They are reported in the table below.

In terms of volume, **Lombardy** is the biggest illicit market (considering drugs, sexual exploitation, ITTP and counterfeiting) with an annual average of about 2 billion euro illicit revenues. In terms of % on GDP, **Campania** records the highest value (1.2%). This region plays a crucial role in the production of illegal goods such as counterfeits (UNODC, 2014) but it is also an important hub (especially the port of Naples) for the trafficking of drugs and illicit tobacco, with a key role played by Camorra groups (Calderoni, 2014a; KPMG, 2015; Transcrime, 2015).

20. Obviously, proceeds generated in one region could be laundered in other areas. However, taking cross-regional flows into account is very difficult given the available data. As mentioned in Chapter 1, the inclusion of illicit market variables is therefore based on the assumption that illicit proceeds are laundered locally. Other variables included in the PCA model will help to mitigate the effect of this strong assumption. Estimates of illicit revenues are preferred to other variables available at sub-national level like administrative or judicial statistics (e.g. number of people arrested for drug trafficking or sexual exploitation, amount of drugs seized, etc.) because the latter are heavily influenced by dark figure biases and geographical patterns (e.g. seizures are higher in areas with ports, airports or at foreign borders) (Levi & van Duyne, 2005; Maguire, 2002; Calderoni, 2014b; Robert, 2009).

21. Transcrime estimates of drugs, prostitution and ITTP are close to 12 billion euros (0.7% GDP) versus 17 billion euros estimated by ISTAT (1% GDP).

Table 7 – Estimates of the revenues of four illicit markets across Italian regions
Illicit drugs (annual average 2008-2012), counterfeiting (2008), ITTP (annual average 2009-2012) and sexual exploitation (annual average 2004-2009). Midpoint estimates

Region	Illicit Drugs		ITTP		Counterfeiting		Sexual Exploitation		TOTAL 4 MARKETS	
	Million euros	% GDP	Million euros	% GDP	Million euros	% GDP	Million euros	% GDP	Million euros	% GDP
Abruzzo	64.1	0.20%	10.5	0.03%	98.9	0.31%	85.3	0.27%	**258.8**	**0.81%**
Basilicata	19.3	0.18%	7.6	0.07%	33.4	0.31%	36.2	0.33%	**96.5**	**0.89%**
Calabria	86.2	0.27%	10.6	0.03%	119.6	0.38%	43.6	0.14%	**259.9**	**0.82%**
Campania	399.8	0.41%	157.0	0.16%	425.4	0.44%	143.2	0.15%	**1125.4**	**1.16%**
Emilia-Romagna	235.3	0.16%	34.5	0.02%	372.8	0.26%	147.0	0.10%	**789.7**	**0.54%**
Friuli - V. G.	43.4	0.12%	15.8	0.04%	121.4	0.34%	170.9	0.48%	**351.5**	**0.98%**
Lazio	261.4	0.14%	55.1	0.03%	434.3	0.23%	520.9	0.28%	**1271.7**	**0.68%**
Liguria	128.7	0.27%	13.8	0.03%	123.8	0.26%	152.3	0.32%	**418.6**	**0.88%**
Lombardy	676.6	0.19%	124.4	0.04%	771.5	0.22%	478.9	0.13%	**2051.3**	**0.58%**
Marche	74.9	0.19%	16.0	0.04%	102.9	0.26%	111.6	0.28%	**305.3**	**0.77%**
Molise	19.3	0.31%	3.8	0.06%	18.9	0.30%	16.6	0.26%	**58.5**	**0.93%**
Piedmont	285.5	0.22%	46.8	0.04%	295.9	0.23%	239.7	0.19%	**867.9**	**0.68%**
Apulia	188.7	0.27%	31.4	0.05%	256.8	0.37%	102.0	0.15%	**579.0**	**0.84%**
Sardinia	129.6	0.40%	16.1	0.05%	101.0	0.31%	33.4	0.10%	**280.1**	**0.86%**
Sicily	193.3	0.23%	30.2	0.04%	307.6	0.36%	126.6	0.15%	**657.6**	**0.78%**
Tuscany	175.6	0.16%	26.3	0.02%	283.8	0.26%	166.3	0.15%	**652.0**	**0.59%**
Trentino / Alto-Adige	51.9	0.04%	8.2	0.05%	79.4	0.00%	96.6	0.07%	**236.1**	**0.16%**
Umbria	38.4	0.18%	8.5	0.04%	60.5	0.00%	134.7	0.62%	**242.1**	**0.84%**
Valle D'Aosta	10.9	0.24%	1.1	0.02%	8.0	0.00%	12.1	0.27%	**32.1**	**0.53%**
Veneto	224.2	0.15%	44.8	0.03%	525.7	0.00%	263.6	0.18%	**1058.3**	**0.36%**
ITALY	**3307.1**	**0.21%**	**662.7**	**0.04%**	**4541.3**	**0.24%**	**3081.4**	**0.23%**	**11592.4**	**0.72%**

Source: Transcrime – UCSC elaboration on Giommoni, 2014; Calderoni et al., 2014; Calderoni, 2014a; Mancuso, 2014.

Corruption, extortion and usury

These crimes play an important role in terms of money laundering in Italy (CSF, 2014). However, they are not included in the model because of difficulties in finding appropriate and reliable measures at sub-national level. They are therefore discussed briefly below.

Corruption

Corruption is related to ML both as a predicate offence (bribes and monetary benefits which are laundered in the legal economy) and a facilitator (e.g. corruption of a bank official to ease the deposit of illicit funds).

In Italy, corruption cases are very often, but not exclusively, related to **public procurement** (Transcrime, 2013; Caneppele, 2014; Fondazione Res, 2014; Fazekas et al., 2016). Despite large-scale judicial investigations in the past (first of all the *Mani Pulite* investigation in the 1990s – see Della Porta & Vannucci, 2007; Vannucci, 2009) and the introduction of a new National Anti-Corruption Authority (ANAC) in 2014, bribery cases are still numerous in public tenders, contracts, and the supply of products and services to local and central public agencies (Golden & Picci, 2006; Mariani, 2015).

Although not overlapping, in Italy there is a close relationship between corruption and criminal infiltration of public procurement. Not by chance, the economic sectors with the highest infiltration levels are those with the largest amounts of public expenditure and procurement - e.g. NACE Sections B, E and F. In this sense, corruption as a ML threat is (only) partially covered in the model by including measures of organised crime.

Extortion and Usury

Extortion and usury play a pivotal role in the economy of Italian Mafias and of foreign OCGs, producing a large amount of illicit proceeds (Lisciandra, 2014; Becucci & Carchedi, 2016). According to estimates at regional level, the revenues from extortion in Campania account for 30% of all the illicit money earned from racketeering in the country as a whole (Di Gennaro & La Spina, 2010). Also usury represents a significant source of illicit proceeds. It has increased in recent years due to the economic crisis, benefiting OC groups which have turned to be lending channels for businesses in financial distress (Marinaro, 2016). According to a recent study, section G (Wholesale & Retail) and section F (Construction) are the business sectors which suffer the most from extortion in terms of revenues in Italy (Rusev et al., 2016, p. 200).

Tax evasion (and underground economy)

According to FATF MER and NRA (FATF, 2016a, p. 17; CSF, 2014a), tax evasion is the **main "proceeds-generating crime"** in Italy. It is therefore a major **ML threat**. However, it is also one of the proxies for the underground economy, which, in the literature on ML risk assessment is often considered to be a vulnerability because it facilitates the concealment of illicit proceeds (FATF, 2013a; Dawe, 2013; Ardizzi, Petraglia, Piacenza, & Turati, 2014; Schneider, 2013).

Tax evasion

According to Confindustria, total tax and contributions evasion in Italy amounted to 122 billion euros in 2015, **equivalent to 7.5% of GDP** (CSC, 2015), a figure in line with the estimates provided by ISTAT on the underground economy (see below). The highest contribution is related to VAT evasion. A study by CASE & CPB indicates that Italy's VAT gap averaged 26% of the total VAT theoretical liability in the period 2000-2011 (CASE & CPB, 2013, pp. 62–63), which puts Italy in the cluster of EU MS with the highest VAT evasion (together with Romania, Lithuania, Slovakia and Greece).

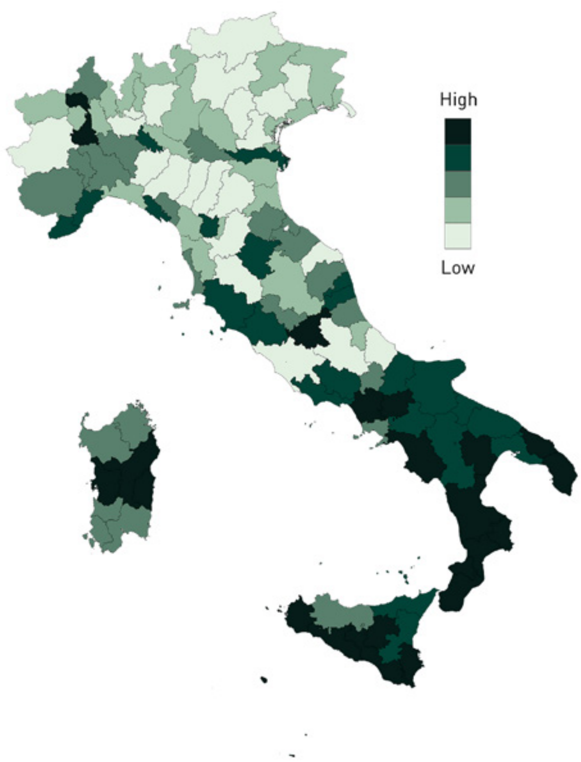
Table 8 – Tax evasion by type
Million euros and % of GDP

Type	Million euros	% GDP
VAT	39,819	2.4
Other indirect taxes	11,402	0.7
IRPEF (personal income tax)	23,449	1.4
IRES (corporate tax)	5,188	0.3
IRAP (regional corporate tax)	3,052	0.2
Local taxes	4,881	0.3
Social contributions	34,418	2.1
Total Tax Evasion	**122,208**	**7.5**

Source: Transcrime – UCSC elaboration of CSC (2015:77)

At sub-national level, tax evasion is operationalized through the tax gap reported by the Italian Revenue Agency - Agenzia delle Entrate (Argentiero, Chiarini, & Marzano, 2015; Braiotta, Pisani, & Pisano, 2012).[22] The map below shows the average tax gap at provincial level in 2001-2009 (data are made available only for this period). The highest levels are recorded in southern provinces, with Vibo Valentia and Agrigento ranking highest. Also some areas of northwestern Italy (e.g. the provinces of Imperia, Savona, Vercelli) show high levels. Important information at regional level can be derived also from the cluster analysis carried out by the Agenzia delle Entrate in 2015 (Carbone & Spingola, 2015), which groups the 110 Italian provinces according to tax evasion patterns.

Figure 6 - Average Tax gap (2001 – 2009)



Source: Transcrime – UCSC elaboration on Agenzia delle Entrate data

22. The tax gap estimated by the Italian Revenue Agency can be defined as the difference between the potential tax levy and the tax that is actually paid. The agency adopts a top-down approach based on comparison between tax data and national account figures provided by ISTAT (for more details see Argentiero, Chiarini & Marzano, 2015, p. 33). No details at regional level on the components of tax gap are available.

Underground economy

Tax evasion is, with irregular labour, the main component of the so-called **underground economy** (which, with illegal activities, constitutes the non-observed economy – EUROSTAT, 2015). ISTAT estimates the underground economy at about 200 billion euros, representing on average 13.1% of Italian value added in the period 2011-2014 (with an increasing trend). Of this figure, 51.4% is attributable to under-declaration and 38.2% to irregular labour (ISTAT, 2016a).

Table 9 - Underground economy components as % of Italian Added Value (2011 – 2014)

	2011	2012	2013	2014
Under-declaration[1]	6.4%	6.8%	6.9%	6.8%
Irregular Labour	4.8%	4.9%	5.0%	5.3%
Other	1.5%	1.3%	1.3%	1.2%
% Italian added value	**12.7%**	**13.1%**	**13.2%**	**13.3%**

Source: Transcrime-UCSC elaboration of ISTAT (2016)

1 Under-declaration is a sub-category of tax evasion and refers to the concealment of income by deliberately misreporting revenues and/or costs ("omissione contributiva")

Information on irregular labour is available at both regional (NUTS 2) and business sector level (see below). Southern Italian regions have the highest ratios of irregular labourers (lavoro nero) to the total number of employees (with Campania (23.4%) and Calabria (21.2%) in the top positions). Among northern regions only Liguria (12.1%) and Friuli Venezia Giulia (10.5%) record ratios higher than 10%.

Money laundering vulnerabilities

Vulnerabilities are identified on the basis of the literature on ML NRA, of available data and proxies at sub-national level (see Chapter 1). They are listed and discussed below.

Table 10 – List of ML-vulnerabilities proxy variables at sub-national area level

ML Risk factor	ML Risk sub-dimension	Proxy variable	Variable label	Source	Disaggregation level	Covered years
Cash-intensiveness	High use of cash	Cash-ratio	*CASH_RATIO*	Transcrime-UCSC elaboration on ABI data	NUTS 3 (Province)	2011 - 2015
		Bank deposits as % of GDP	*BANK_DEPOSITS*	Banca d'Italia	NUTS 3 (Province)	2014
		Point of sales (POS) per capita	*POS_NUMBER*	ABI	NUTS 3 (Province)	2011 - 2015
Opacity of business ownership	Complexity of business ownership structure	BO distance	*BO_DISTANCE* *BO_DISTANCE_w* [a]	Transcrime-UCSC elaboration on BvD data	NUTS 3 (Province)	Last available year
	Ownership links with risky jurisdictions	BOs' risk score	*RISKY_BENEFICIAL_OWNERS* *RISKY_BENEFICIAL_OWNERS_w* [a]	Transcrime-UCSC elaboration on BvD and TJN data	NUTS 3 (Province)	Last available year
		Shareholders' risk score	*RISKY_SHAREHOLDERS* *RISKY_SHAREHOLDERS_w* [a]	Transcrime-UCSC elaboration on BvD and TJN data	NUTS 3 (Province)	Last available year
Other vulnerabilities	High volume of money remittances	Money remittances as % GDP	*REMITTANCES*	Transcrime-UCSC elaboration on Banca d'Italia and Eurostat	NUTS 3 (Province)	2011 – 2013
	Presence of transit hubs	Number of transit hubs	*TRANSIT_HUB*	Transcrime-UCSC elaboration	NUTS 3 (Province)	-
Control variables and ML measures – used to validate the indicator						
	ML measures	STRs / N. Bank agencies	*STR_BANK*	Elaboration on UIF and ABI data	NUTS 3 (Province)	2012 - 2014
		ML offences / Population	*ML_OFFENCES*	Ministero dell'Interno – ISTAT	NUTS 3 (Province)	2004 - 2013
	Controls	GDP (market prices)	*GDP*	Eurostat	NUTS 3 (Province)	2009 - 2013
		GDP per capita (market prices)	*GDP_PC*	Eurostat	NUTS 3 (Province)	2009 - 2013
		Population	*POPULATION*	Eurostat	NUTS 3 (Province)	2001 - 2014

[a] *Variables ending with "_w" are weighted for the average company size in the area so as to control for the presence of multinational companies (see below and Annex for details)*

Source: Transcrime – UCSC elaboration

Cash-intensiveness

As described in Chapter 1, **cash-based economies are more vulnerable** to money laundering. Cash is a facilitator for committing crimes (first of all tax evasion) and for concealing and laundering the proceeds of crime (Riccardi & Levi, 2017; Europol, 2015; U.S. Department of the Treasury, 2015; Soudijn & Reuter, 2016). Italy is one of the EU MS with the highest levels of cash use (see table below), which therefore represents a major ML vulnerability in the country (CSF, 2014a, p. 8). The use of alternative (and more traceable) payment methods is still infrequent, even though the diffusion of point of sales **(POS) terminals in Italy is the second highest** in Europe (see Table 12 below - ECB, 2016), whose use, however, may be hampered by the high fees for merchants and retailers.

In order to reduce the use of cash, in recent years the maximum threshold for cash payments has been revised down from 12,500 euros in 2008 to 1,000 euros. Since 1 January 2016, cash payments are only allowed up to 3,000 euros (Legge di Stabilità, 2016). The same law has also introduced requirements on merchants and professionals to accept payments with debit and credit cards, although implementation decrees have not yet been introduced.

Table 11 - % purchases made in cash by price range

	< 20 euros	30 - 100 euros	200 - 1000 euros	> 10.000 euros
Europe	87%	55%	20%	4%
Belgium	84%	48%	18%	5%
Germany	91%	69%	21%	4%
Spain	90%	64%	30%	6%
France	80%	15%	3%	0%
Italy	91%	77%	31%	4%
Luxembourg	77%	27%	10%	3%
Netherlands	65%	20%	8%	4%
Austria	82%	60%	29%	10%

Source: Transcrime – UCSC elaboration of ECB (2011)

Table 12 – Number of POS terminals provided by resident payment service providers
Ratio on population. First 10 EU countries - 2015

EU countries	POS terminals per million inhabitants
Luxembourg	260,596
Italy	32,596
United Kingdom	30,077
Spain	29,841
Finland	27,985
Portugal	27,645
Cyprus	26,931
Netherlands	26,273
Denmark	24,639
Croatia	24,551
EU AREA (median)	**18,758.47**

Source: Transcrime – UCSC elaboration of ECB (2016: 54)

The level of cash use across Italian provinces is measured through three different proxies:

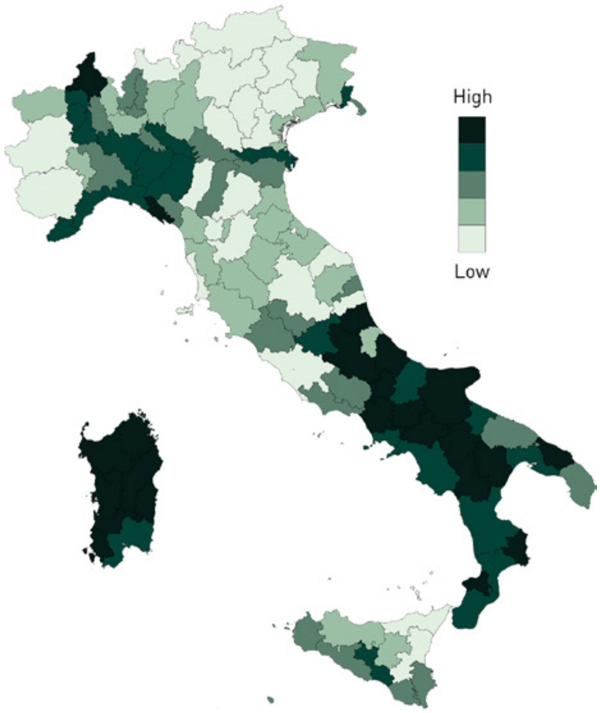
- The so-called ***cash-ratio*** (Ardizzi & Iachini, 2013);[23]
- The number of **POS per capita**;
- The amount of **bank deposits** as % of the GDP;

While the first two are indirect measures of cash use (versus other payment methods like credit and debit cards), the third can be taken as a measure of the degree of integration of citizens' wealth in the financial system (Ardizzi & Iachini, 2013; Ardizzi et al., 2014). The assumption is that the higher the cash-ratio, the lower the number of POS per capita; and the lower the % of bank deposits on GDP, the higher the ML risk.

Sardinia (especially the provinces of Ogliastra, Carbonia-Iglesias and Sassari) and **Calabria** (Crotone, Vibo Valentia) are the regions with the highest cash-ratio (in the period 2011-2015). These spatial patterns are confirmed by that of POS distribution and of bank deposits, where southern Italian provinces (especially Calabrian ones) show low figures.

The extent of cash use may be determined both by legal factors (e.g. the share of elderly people, the nature of the local business structure) and illegal ones (e.g. the level of tax evasion and underground economy). A recent study by the Bank of Italy (Ardizzi, De Franceschis, & Giammatteo, 2016) on **'anomalous' cash use** shows a negative correlation between cash adoption and level of education and financial literacy: *"confidence in alternative payment instruments, being positively correlated with higher general education and financial literacy, leads to a lower use of cash"* (Ardizzi et al., 2016, p. 21) but a positive correlation with criminal intensity and money-laundering measures.

Figure 7 Cash-ratio (average 2011-2015)



Source: Transcrime – UCSC elaboration of ABI data

Opacity of business ownership structure

The opacity of corporate structures, although widely acknowledged as a **key ML vulnerability** (see Chapter 1 - (FATF, 2016b, 2014a; ECOLEF, 2013; Riccardi & Savona, 2013; de Willebois et al., 2011) **is very hard to operationalise** and measure. IARM focuses on two sub-dimensions:

- The **level of complexity** of Italian businesses' ownership structure as such;
- The volume of business ownership connections with shareholders and BOs from **risky jurisdictions**.

23. Cash-ratio is an indirect proxy for cash use. It measures the ratio between the economic value of ATM withdrawals, taken as a proxy for cash use, and the sum of the total value of POS operations (i.e. with credit and debit cards) with ATM withdrawals (Ardizzi & Iachini, 2013). For the purposes of this study only operations with debit cards are considered.

Level of complexity of Italian businesses' ownership structure

A good measure of business ownership complexity is the so-called **BO distance**, provided by Bureau van Dijk (BvD), which represents the number of 'steps' which separate a company from its beneficial owner(s).[24] The greater the BO distance, the more complex the ownership structure, and the higher the ML risk. A higher complexity makes it more difficult to trace actual beneficial owners, who can more easily conceal illicit funds. Information on the BO distance of Italian companies is collected and then aggregated for each registered company; averages have been then computed by area or business sector.

On average, each of the 3.7 million Italian companies in the database has 1.42 shareholders, a value lower than in other EU MS. The figure would be even lower after including other types of legal forms like unlimited companies or individual enterprises (not widely covered by the dataset). Moreover, the average BO distance is close to one (1.21)[25] which denotes, generally, a simple and almost direct control of Italian companies. Indeed, more than 50% of Italian companies are individual enterprises.

Despite this general pattern, the complexity of the business ownership structure varies across regions and business sectors. Large urban provinces and areas on foreign borders are usually characterized by greater BO distance (e.g. Imperia 1.5, Savona 1.4, Bolzano and Milano 1.4). This may be due to the higher number of FDI and multinational companies. For this reason, in order to control for the effect of multinationals and identify the actual anomalies, the BO distance in each area is weighted by the average company size in that area (see Annex for details). As a result, the scores of large urban areas decrease, while provinces on the border still rank high (see map below). In the south, Catanzaro ranks high, representing an outlier with respect to other southern areas.

Table 13 – Data on ownership of Italian businesses, by nationality of shareholder and BO

	Italian	Foreign	Nationality not available	TOTAL ITALY
N. Companies[26]	-	-	-	3,669,902
N. Shareholders	2,542,091 (48.7%)	44,971 (0.9%)	2,634,204 (50.5%)	5,221,265
N. Legal person shareholders	404,834	29,733	-	434,566
% Legal persons/Tot. Shareholders	15.9%	66.1%	-	16.8%
N. Beneficial Owners	1,994,735 (42.4%)	26,500 (0.6%)	2,687,697 (57.1%)	4,708,932
Ratio Shareholders/Companies	-	-	-	1.4
Ratio Beneficial owners/Companies	-	-	-	1.3
Ratio Shareholders/Beneficial owners	1.3	1.7	1.0	1.1
Beneficial ownership distance (average)	-	-	-	1.2

Source: Transcrime – UCSC elaboration of BvD data

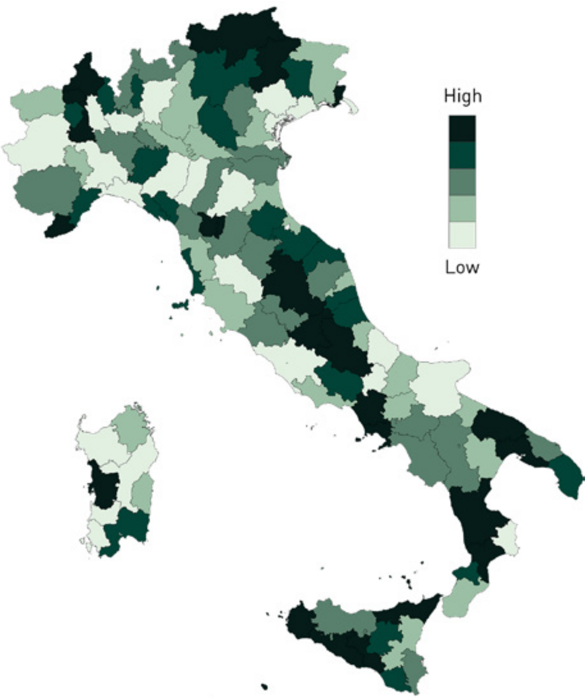
24. BOs in the BvD definition are the individual(s) who ultimately own or control a company or other legal entity. BvD identifies them by reconstructing the ownership chain until finding natural persons holding above a certain shareholding. For the purpose of this study, it has been decided to set the minimum threshold at 10% of the shareholding at the first level of the company ownership chain and 10% at further levels. The threshold adopted is lower than that indicated by the current EU Directive's definition (25%) but allows for a more comprehensive analysis. When BO distance equals 1, the company is directly controlled by its BO(s) (see Annex for details).

25. This value is calculated as the average BO distance across Italian provinces. It is 1.34 if calculated as the average across Italian business sectors (see Chapter 5)

26. Although the Bureau van Dijk (BvD) AIDA and ORBIS databases cover almost the entire universe of the 6 million Italian companies, ownership information is available only for about 3.7 million companies, i.e. those legal forms (like limited companies) which are required to file ownership information with the business registry.

Figure 8 – Average BO distance across Italian province

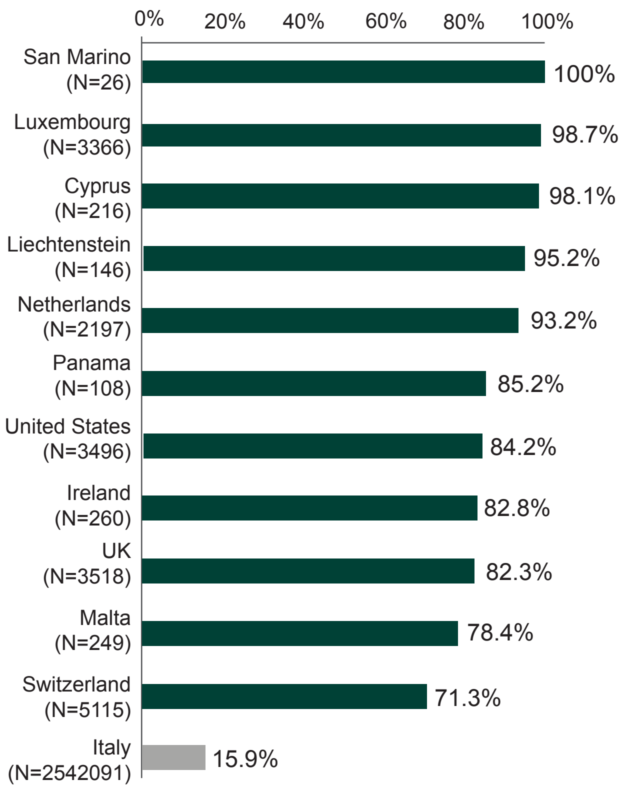
Weighted by average company size



Source: Transcrime – UCSC elaboration of BvD data

Figure 9 - % legal person shareholders on total shareholders by nationality

Selected nationalities with at least 20 shareholders. In brackets number of shareholders by each nationality



Source: Transcrime – UCSC elaboration on BvD data

Another proxy for complexity is the percentage of legal persons among shareholders. The higher the number of companies as shareholders, the more difficult it is to trace the ultimate owner. Legal persons[27] represent 16.8% of the total number of shareholders of Italian companies. It is interesting to note that the percentage is much **lower among Italian shareholders (15.9%) than foreign ones (66.1%)**. In particular, according to the data provided by BvD, there are no natural person shareholders from **San Marino (100% are legal entities)** while Luxembourg (98.7%), Cyprus (98.1%), Liechtenstein (95.2%) show similar patterns (Table 8). Notably, the percentage of natural persons among Swiss shareholders is significant (28.7%) and can also refer to Italian individuals who have moved their tax residence to Switzerland.

Business ownership connections with risky jurisdictions

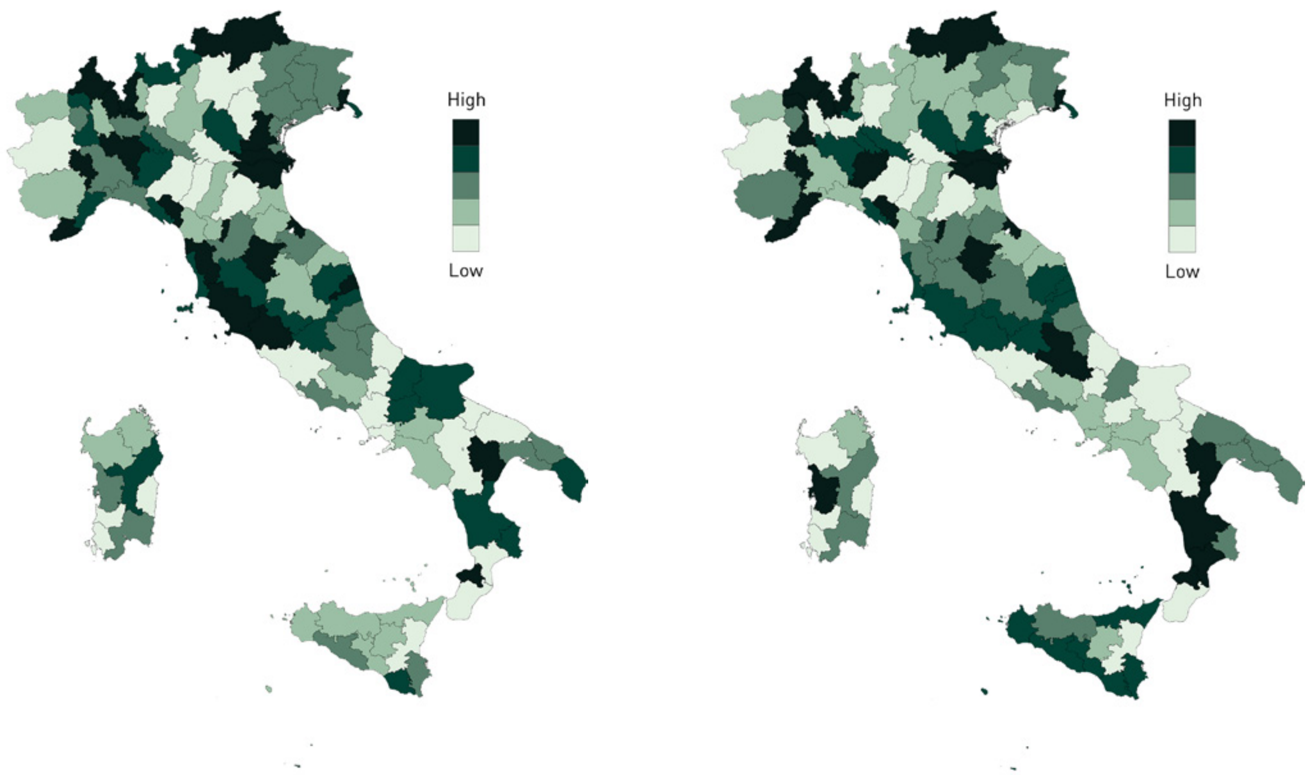
The connections with 'risky jurisdictions' can be understood by considering the average level of risk and opacity of the nationalities of shareholders and BOs of Italian companies. In order to calculate it, the % of foreign shareholders and BOs in each province and in each business sector is multiplied by an **indicator of opacity and low transparency (the Secrecy Score of the Financial Secrecy Index, henceforth FSS)**.[28]

27. BvD distinguishes among 15 types of shareholders: Insurance company; Bank, Trade & Industry organisation; Nameless private stockholders; Mutual & Pension fund / Nominee / Trust / Trustee, Financial company; One or more named individuals or families; Foundation / Research Institute; Other named shareholders; Employees/Managers/Directors; Private Equity firms; Public authority/State/Government; Venture Capital; Hedge funds and Public (Publicly listed companies). Legal persons are here considered to be all types of shareholders excluding individuals and families.

28. The Secrecy Score is a component of the Financial Secrecy Index (FSI) developed by the Tax Justice Network. It is a composite indicator which evaluates different dimensions of secrecy in the financial sector and in the legislation of selected jurisdictions. In particular, it evaluates: A) the level of banking secrecy; B) access to beneficial ownership information; C) corporate transparency; D) efficiency of tax and financial regulation; E) compliance with international standards; F) international cooperation (Tax Justice Network, 2015). For further details see Chapter 5 and Annex. The secrecy score has been preferred to other measures of risky jurisdictions (e.g. international or national blacklists) because of its independency and transparency of the evaluation methodology. For the purpose of the study the acronym FSS is used.

Figure 10 – Level of business ownership connections with risky jurisdictions

Shareholders' risk score (left) and BOs' risk score (right). Weighted by average company size



Source: Transcrime – UCSC elaboration of BvD and TJN data

This indicator was used also in previous studies (Cassetta, Pauselli, Rizzica, & Tonello, 2014; Gara & De Franceschis, 2015; Riccardi, Milani, & Campedelli, 2016). In particular, each nationality is weighted by the relevant value of the FSS, and again corrected with a measure of company size to control for the presence of multinational companies (see Annex for details).

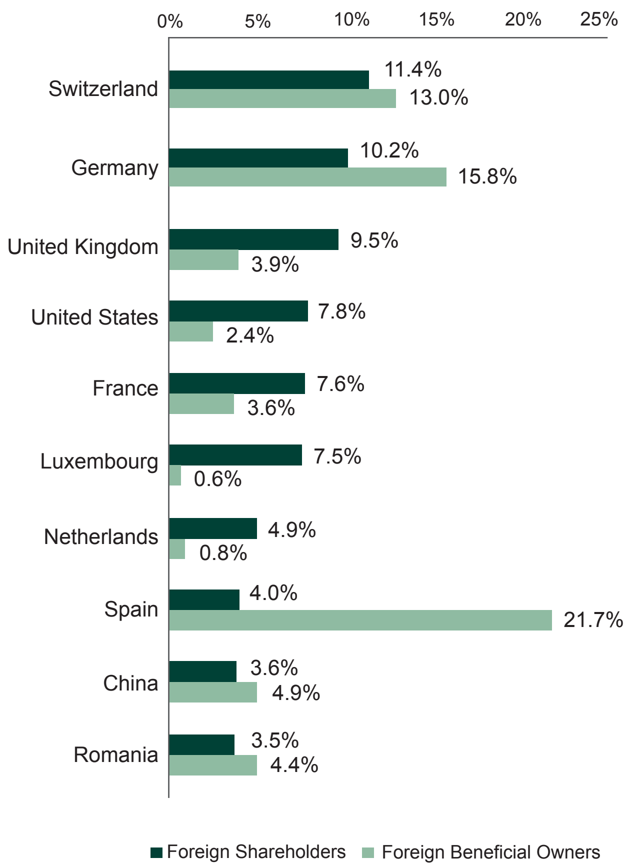
At area level, the provinces with highest risk score for shareholders are **Imperia, Bolzano, Como and Gorizia**. For beneficial owners, they are Catanzaro, Imperia, L'Aquila and Bolzano. Again, border areas rank high even after controlling for average company size.

Foreign shareholders represent only 1% of the total number of shareholders in Italy (1.7% excluding those with no information on nationality - see the above table). Italy registers much lower percentages than other EU MS (e.g. among IARM countries: 7.8% of shareholders of Dutch companies are foreign, 9.1% of UK ones).

Switzerland is the first nationality represented (5,115 between natural and legal persons, 11.4% of all foreign shareholders) followed by Germany, UK, US, France, Luxembourg and the Netherlands. These nationalities also rank high when considering only legal person shareholders (see Annex). In terms of **BOs**, surprisingly the most frequent nationality is **Spain**, followed by Germany and Switzerland. Spanish BOs are numerous in various provinces (e.g. Catanzaro, L'Aquila, Vercelli, Milan or Bolzano) a situation which is not easy to explain and warrants further research (see box below for some possible interpretations).

Figure 11 – Foreign shareholders and BOs by nationality

First 10 nationalities (% of total foreign shareholders and BOs)

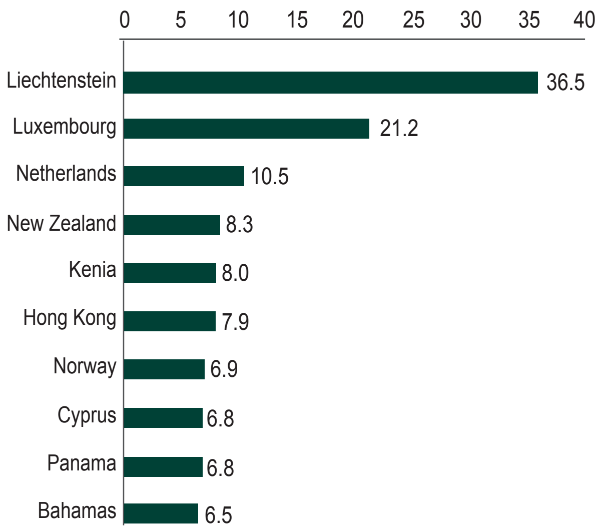


Source: Transcrime – UCSC elaboration of BvD data

On considering the ratio between shareholders and beneficial owners, the statistics change substantially. The **jurisdictions at the top are Liechtenstein, Luxembourg and Netherlands.** It can be assumed that the higher the ratio, the more likely it is that companies established in that country play a role as holding companies to respond to tax optimisation and other corporate drivers.

Figure 12 – Ratio shareholders/BOs of Italian companies

First 10 nationalities with highest value



Source: Transcrime – UCSC elaboration of BvD data

The anomalous number of Spanish beneficial owners

According to BvD data, the most represented nationality among foreign BOs in Italy is Spanish: 21.7% of total foreign beneficial owners (see Figure 7). This number is difficult to explain because it does not fully mirror the relatively low volume of FDI from Spain, nor the size of the Spanish community in Italy.

Although, in terms of absolute values, Milan and Rome record the highest number of Spanish BOs, **values are relatively higher in Southern provinces**, especially Catanzaro (95% of total foreign BOs), L'Aquila (87.2%), Nuoro (66.7%), Caserta (65.3%) and Naples (64.0%).

Spanish BOs are very numerous in divisions R92 (Gambling and betting activities), E36 (Water collection, treatment and supply), C18 (Printing and reproduction of recorded media) and F42 (civil engineering). To be noted is that, in the gambling sector, recent investigations have revealed that mafia organisations (especially Camorra, but also 'Ndrangheta) have channelled and laundered money through companies established in Spain and Malta – as highlighted, for example, by the so-called “*Gambling*” investigation (Vita, 2015). Also to be noted is that the Camorra is very present in Spain (Palomo, Márquez, & Laguna, 2016) and, besides betting agencies, also other sectors listed in the Table below - such as waste and water collection, manufacture of food products, construction and building and landscape activities – have been frequently involved in investigations against the Camorra.

Although the link with organised crime could be a hypothesis to explain this anomaly, it should be considered that also in the other two IARM countries (Netherlands and UK) Spain is the most represented foreign jurisdiction with respect to BOs. This figure should therefore be investigated further.

Table 14 – Spanish BOs in Italy
Top 10 divisions
Last available year

Business Sector (NACE division)	% Spanish BOs/ Foreign BOs
R 92. Gambling and betting activities	86.6%
E 36. Water collection, treatment and supply	85.7%
C 18. Printing and reproduction of media	78.8%
F 42. Civil engineering	75.4%
C 10. Manufacture of food products	74.0%
D 35. Electricity, gas and air conditioning supply	71.6%
R 93. Sports activities and amusement	58.4%
N 81. Services to buildings and landscape activities	52.2%
K 64. Financial service activities	47.7%
J 61. Telecommunications	43.8%

Source: Transcrime – UCSC elaboration of BvD data

Other ML vulnerabilities

Money transfers

Other ML vulnerabilities considered by the analysis are the volume of money remittances and the presence of transit hubs. As regards the former, according to experts, r**emittance services and money transfer businesses** (MTBs) can be misused for ML or TF purposes (CSF, 2014a; FATF, 2016c). In particular it is stressed that the distribution of MTBs **outside the financial sector** (e.g. travel agencies, bars, tobacco shops, internet points and call centres, etc.) may make thorough monitoring more difficult (Clemente, 2016; Maresca, 2016; CSF, 2014a, p. 23). Moreover, the **complex and fragmented EU regulatory framework** in the money transfer domain makes it often difficult for Italian authorities to monitor those EU intermediaries which operate in the country but are subject to foreign agencies’ supervision (*home-country control principle*). In this regard, to be noted is that in recent years numerous intermediaries (*IP – istituti di pagamento*) have relocated outside Italy (keeping local agencies in the country), being induced to do so by lower compliance requirements and tax advantages (Clemente, 2016, p. 6-8).

In terms of average value of money remittances as % GDP, besides the biggest cities (Rome, Milan, Florence, Naples), **Prato** records the highest volume due to the high presence of Chinese businesses and nationals, followed by Imperia.

Transit hubs

Transit hubs are measured by means of a categorical variable at province level taking into account the presence of ports and airports and of borders with non-EU countries, i.e. Switzerland, San Marino, Holy See (see Annex for details). It is assumed that the presence of these patterns – especially of ports and borders – can increase the risk of illicit financial flows such as cash-smuggling (DIA, 2015; DNA, 2014; Bernasconi, 2012; MEF, 2014).

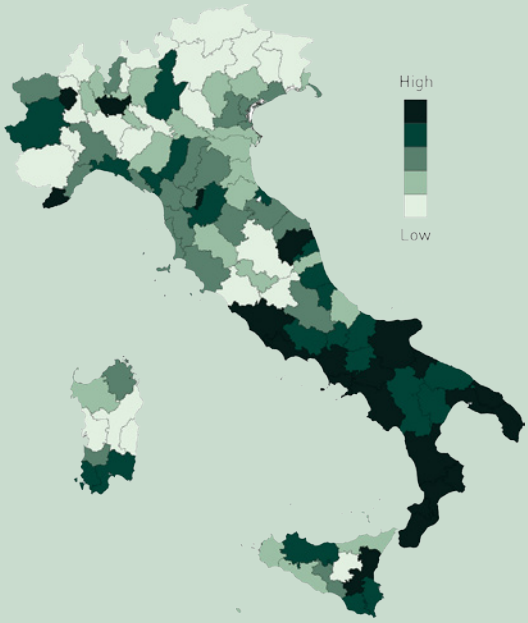
All those presented above are indirect measures of ML risk. But are other proxies and evidence of ML available in Italy? And what do they tell us?

A first measure to consider is the volume of **STRs - suspicious transaction reports** (*SOS - segnalazioni operazioni sospette*) issued by obliged entities in compliance with the national AML regulation, and in particular with Legislative Decree no. 231/2007. The Italian FIU (*UIF – Unità di Informazione Finanziaria*) produces periodic reports with detailed statistics on STRs, to which the reader is referred.

STRs have **steadily increased in the past few years**, rising from 67,047 in 2012 to 82,428 in 2015. Although most of the reports are issued by banks and financial intermediaries (above 90%), the weight of professionals and other non-financial operators is growing (UIF, 2016b). Part of the increase in STRs by professionals may be related to the recent adoption of the so-called ***Voluntary Disclosure*** procedure (Law 15 December 2014, no. 186) (UIF, 2016a, 2016b)

The map (Figure 13) shows the **number of STRs** (average 2012-2014) weighted by the number of bank agencies (which, as discussed, issue more than 90% of all STRs in the country) across Italian provinces (by province of origin of the STR). Large urban areas (Rome, Milan, Naples, Turin) show higher ratios, along with southern regions. Also Prato and Imperia show high levels. This variable will be used to validate the composite indicator of ML risk (see Fig. 13).

Figure 13 - Suspicious transactions reports (STRs) per bank agency
Average 2012-2014. Italian provinces



Source: Transcrime – UCSC elaboration of Banca d'Italia – UIF data

Table 15 - Suspicious Transactions Reports (STRs) by category of obliged entity

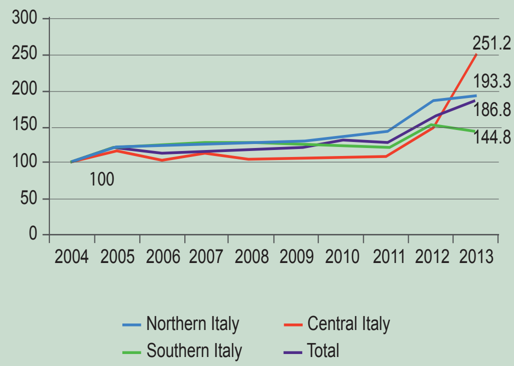
	STRs 2012		STRs 2013		STRs 2014		STRs 2015	
Banks and financial intermediaries	64,677	96.5%	61,765	95.6%	68,220	95.1%	74,579	90.5%
Professionals	1,988	3.0%	1,985	3.1%	2,390	3.3%	5,979	7.3%
Non-financial operators	382	0.6%	851	1.3%	1,148	1.6%	1,864	2.3%
Other	0	0.0%	0	0.0%	0	0.0%	6	0.0%
TOTAL STRs received	**67,047**	**100%**	**64,601**	**100%**	**71,758**	**100%**	**82,428**	**100%**

Source: Transcrime – UCSC elaboration on Banca d'Italia – UIF data

Also **administrative statistics on money laundering** in Italy – and in particular data on ML offences recorded by the police or on people prosecuted/sentenced for ML – are available, but they only partially measure the problem. Money laundering (like other economic crimes such as corruption or usury) has a **very high dark figure** (FATF, 2015a; Unioncamere, 2013). Furthermore, until 2015 the Italian Criminal Code did not cover self-money laundering, and this had a strong impact in terms of the representativeness of crime statistics.

Nevertheless, in recent years the **number of ML offences has been steadily growing**, registering a 100% increase in a 10-year time span (from 977 in 2004 to 1,825 in 2013; 3.1 on 100,000 inhabitants). In particular, central Italy has recorded a 250% growth, while the upward trend in Southern Italy has been less strong. Given the 2015 introduction of the **self-laundering** offence in the Italian Criminal Code (art. 648 ter. 1), it is possible that prosecutions and sentences for ML will increase further.

Figure 14 – ML offences per macro region. Index 2004=100



Source: Transcrime – UCSC elaboration of ISTAT data

STEP 3 – DATA COLLECTION AND NORMALISATION

Data collection, cleaning, imputation of missing value, validation

For each identified proxy variable, **data are collected** from the relevant sources. When not publicly available, information was requested from the relevant authority, institution or data provider. In most cases, variables were already available at province (NUTS 3) or region (NUTS 2) level. In other cases, for instance business ownership, microdata (e.g. at individual company level) are collected and then aggregated by province or business sector.

Due to limited data availability, different variables are covered with different time spans. **2011 is the median year** of the variables collected, but more than 50% have data covering 2014 or 2015. **Missing data** across provinces are usually replaced with weighted averages of neighbouring provinces (see Annex for details).

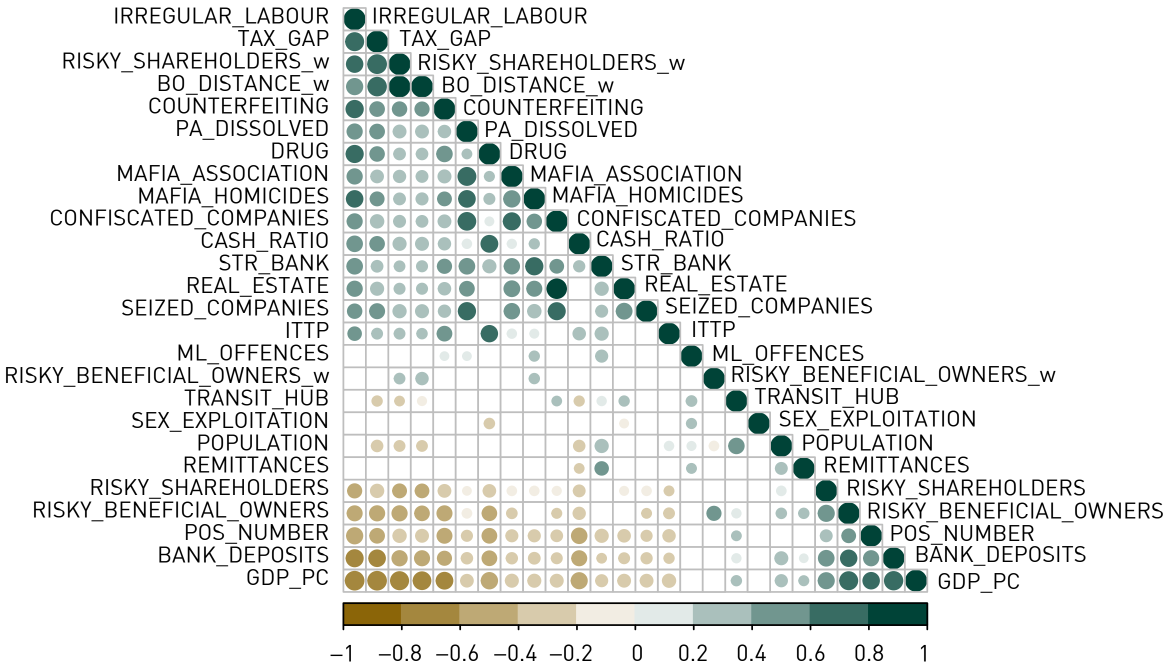
Data transformation and normalisation

The IARM methodological approach relies on the **concept of *relative risk*** (see above), which means that the level of ML threats or vulnerabilities is weighted for the size of the local population and/or the economy (e.g. ratio on the provincial GDP). The arithmetic mean of the ratios is then calculated for the available years.

STEP 4 – DATA EXPLORATION AND CORRELATION ANALYSIS

All the RF discussed above help to understand ML risk components in Italy. However, if taken alone, they appear to be not very meaningful: in order to capture the **overall risk**, it is necessary to **compare and combine all the components together in a synthetic measure of ML risk**. This is the aim of the next phases (Steps 4-7), where a composite indicator of ML risk, condensing all the ML threats and vulnerabilities discussed so far, is constructed and validated.

Figure 15 – Pearson correlation among identified proxy variables at province level



Source: Transcrime – UCSC elaboration

In order to do so, ML RF variables are first explored through descriptive statistics and basic inference tests to identify specific patterns in the data. Several variables are **characterized by outliers** (e.g. some southern provinces with respect to organised crime measures). Since PCA is not constrained to any specific data distribution (OECD & JRC, 2008), variables are kept in their value without omitting outliers or treating data with smoothing/centring techniques. Then the analysis of correlation is carried out to understand if and which variables share common patterns. The **linear Pearson correlation** among the identified variables is presented in the correlogram below. Non-significant correlation coefficients (α = 10%) are left blank, whereas the colours denote significant correlations (green positive, red negative). The colour intensity is stronger, the higher the correlation coefficient.

It can be noted that most of the proxies for **ML threats and vulnerabilities are generally positively and strongly correlated**. Important ML vulnerabilities such as cash-intensiveness are closely correlated with both OC measures and tax evasion/underground economy proxies (e.g. tax gap and irregular labour). Illicit markets are all correlated, except for sexual exploitation. As hypothesised, high levels of cash use (measured through the cash-ratio) are recorded in provinces where the number of per capita POS terminals and the level of integration of population wealth in the financial system (measured as % bank deposits on GDP) are low. The measures of the **opacity of business ownership** (i.e. *BO_DISTANCE, RISKY SHAREHOLDERS AND RISKY BENEFICIAL OWNERS*) are correlated only when weighted by average company size (so as to control for the presence of multinationals and identify actual anomalies).[29]

The number of **suspicious transaction reports per bank agency** (STR_BANK) has a strong and positive correlation with most of the threats and vulnerabilities identified, e.g. mafia measures, cash-intensiveness and proxies for the underground economy. STRs tend to be higher also in provinces/areas where the GDP per capita and the integration of the real economy into the financial sector (BANK_DEPOSITS) are lower. On the other hand, **ML offences** (ratio on the population) show a positive correlation with STRs but a weak or no linear correlation with threat and vulnerabilities proxies. The result confirms what suggested above, i.e. that this measure could be not fully meaningful and representative of the ML phenomenon for various reasons and bias.

29. If unweighted, the proxies for ownership opacity are not positively correlated with other threats and vulnerabilities, and are not correlated with STRs, while are positively correlated with measures of financial development such as GDP per capita and the % of deposits on GDP. This confirms the idea that, when not weighted, opacity proxies are rather a measure of the presence of multinational companies and of the volume of FDI.

STEP 5 - PRINCIPAL COMPONENT ANALYSIS (PCA)

To develop the composite indicator of ML risk, as mentioned in Chapter 1, it is decided to adopt a **principal component analysis** (PCA) approach.[30] This helps to downsize the number of variables into a smaller number of components (Kabacoff, 2015; OECD & JRC, 2008; Jolliffe, 2002), which would correspond to sub-dimensions of ML risk. The PCA is carried out as follows:

1. First, variables showing non-significant linear correlations with most of the other variables (e.g. sexual exploitation, risky BOs, transit hubs) are dropped. Also STRs, ML offences and other controls are dropped because they are used to validate the final composite indicator (see STEP 7). Remittances are kept due to the strong positive relationship with STRs. As a result, **17 variables are included** in the PCA;
2. The **number of principal components** (PCs) is selected on the basis of generally accepted standards – e.g. the so-called Kaiser-Harris criterion (see Kabacoff, 2015; OECD & JRC, 2008; Rencher, 2002);
3. Extracted PCs are **identified, 'labelled' and discussed.** It is also checked if the structure of PC confirms the theoretical framework of risk factors described above (see STEP 1);
4. PCs are then aggregated using as weights **the proportion explained** in the PCA (see STEP 6).

The results of the PCA are summarised in the table below (matrix of rotated components).

Table 16 - Principal component analysis. Matrix of rotated components (Varimax rotation)

Variable	PC1	PC2	PC3	PC4	PC5
TAX_GAP	0.4	0.73	0.06	0.16	-0.05
IRREGULAR_LABOUR	0.5	0.69	0.35	-0.03	-0.03
BANK_DEPOSITS	-0.17	-0.83	-0.01	0.04	0.05
POS_NUMBER	-0.21	-0.71	-0.19	0.14	-0.01
CASH_RATIO	-0.02	0.72	0.31	0.17	-0.17
DRUG	0.03	0.6	0.63	-0.11	-0.08
ITTP	0	0.21	0.84	-0.11	-0.03
COUNTERFEITING	0.34	0.47	0.5	-0.16	0.1
RISKY_SHAREHOLDERS_w	-0.11	-0.03	-0.13	0.86	0
BO_DISTANCE_w	0.06	0.03	-0.04	0.89	0.04
REMITTANCES	0.02	-0.13	-0.03	0.05	0.97
REAL_ESTATE	0.79	0.21	-0.1	-0.06	-0.03
CONFISCATED_COMPANIES	0.88	0.15	-0.04	-0.12	-0.03
SEIZED_COMPANIES	0.76	0.24	-0.19	-0.11	0.12
MAFIA_HOMICIDES	0.69	0.17	0.33	0.21	0.06
PA_DISSOLVED	0.84	0.13	0.14	0.09	-0.02
MAFIA_ASSOCIATION	0.81	0.08	0.25	-0.06	0

SS loadings	4.41	3.53	1.89	1.74	1.02
Proportion variance	0.26	0.21	0.11	0.10	0.06
Cumulative variance	0.26	0.47	0.58	0.68	0.74
Proportion explained (Pi)	0.35	0.28	0.15	0.14	0.08
Cumulative proportion	0.35	0.63	0.78	0.92	1

Source: Transcrime – UCSC elaboration

30. Principal component analysis is a multivariate data analysis technique used, in a similar way to other approaches (e.g. factor analysis), to reduce the information contained in large datasets to a smaller number of components (or factors, in factor analysis), each of them able to summarise a specific phenomenon explained by a range of correlated variables. For this purpose, PCA uses an orthogonal transformation of the correlated variables into a set of principal components which are uncorrelated with each other (OECD & JRC, 2008; Jolliffe, 2002).

The PCA **confirms the theoretical approach suggested above**. It identifies **five principal components** (all with eigenvalues >1 – the overall model captures 74% of data variability) which support, with empirical evidence, the system of ML risk factors, dimensions and sub-dimensions discussed in previous paragraphs. The PCA also confirms what the 2014 NRA and 2016 FATF MER presented as the three main ML risk issues in Italy: mafia organised crime (PC1), illicit markets (PC3), tax evasion and cash-intensiveness (both in PC2). The PCs are discussed and presented in the maps below.

PC1

Principal component 1 (PC1) – Organised crime presence and infiltration

This component groups together the set of OC threat variables and in particular proxies for **mafia presence and infiltration** in the legitimate economy. According to our model, it is the most significant component of the ML risk in Italy because on its own it explains 26% of all data variability and 35% of model variance.[31] It can be noted that it is also positively correlated with irregular labour and tax gap.

The map below represents the values of PC1 extracted for each Italian province and classified according to deciles. Those with highest values are in the South, and in particular in **Sicily, southern Calabria** (Reggio Calabria, Vibo Valentia, Catanzaro, Crotone), Campania (**Naples and Caserta** in particular) and **southern Lazio** (Latina, Frosinone, Rome). In the North, Milan also scores high (see Part 2).

31. Calculated as the ratio between the proportion of variance (0.26) and the total cumulative variance (0.74).

PC2

Principal component 2 (PC2) – Underground and cash-intensive economy

The second component groups together proxies for the **underground economy** (tax gap, as a measure of tax evasion, and irregular labour) and measures of the **cash-intensiveness** of Italian provinces (the cash-ratio and, with negative sign as expected, distribution of POS terminals and the % on GDP of bank deposits). Estimates of illicit markets revenues are also positively correlated with this PC, confirming a strict relationship between the underground and the illegal economies (ISTAT, 2016a; EUROSTAT, 2015; OECD, 2002). PC2 represents the second most significant component, explaining 28% of the variance of the entire model. With few exceptions, **southern provinces** register high values. Also **Sardinia and Liguria** rank high. Not surprisingly, provinces of the biggest cities in Italy (Milan, Rome, Naples, Turin, Bologna) record low values due to the lower cash-use and the higher financial integration of people's wealth.

PC3

Principal component 3 (PC3) – Illicit markets

Interestingly, in our PCA the measures of the **three illicit markets** covered by the analysis (drug trafficking, counterfeiting, illicit trafficking of tobacco) group together in a single component which represents the third dimension of ML risk in terms of variance explained (15% of the model). The PC is also positively correlated with measures of OC threat and of cash-intensity. Although all the three markets have regional estimates, it is possible to extract from the PCA values at provincial level (because of the contribution of the other variables in the model), which are presented in the map below. All **provinces of Campania** record very high values. Also Sardinia and southern Calabria rank high on PC3, and so do big cities (e.g. Milan, Naples, Rome).

PC4

Principal component 4 (PC4) – Opacity of business ownership

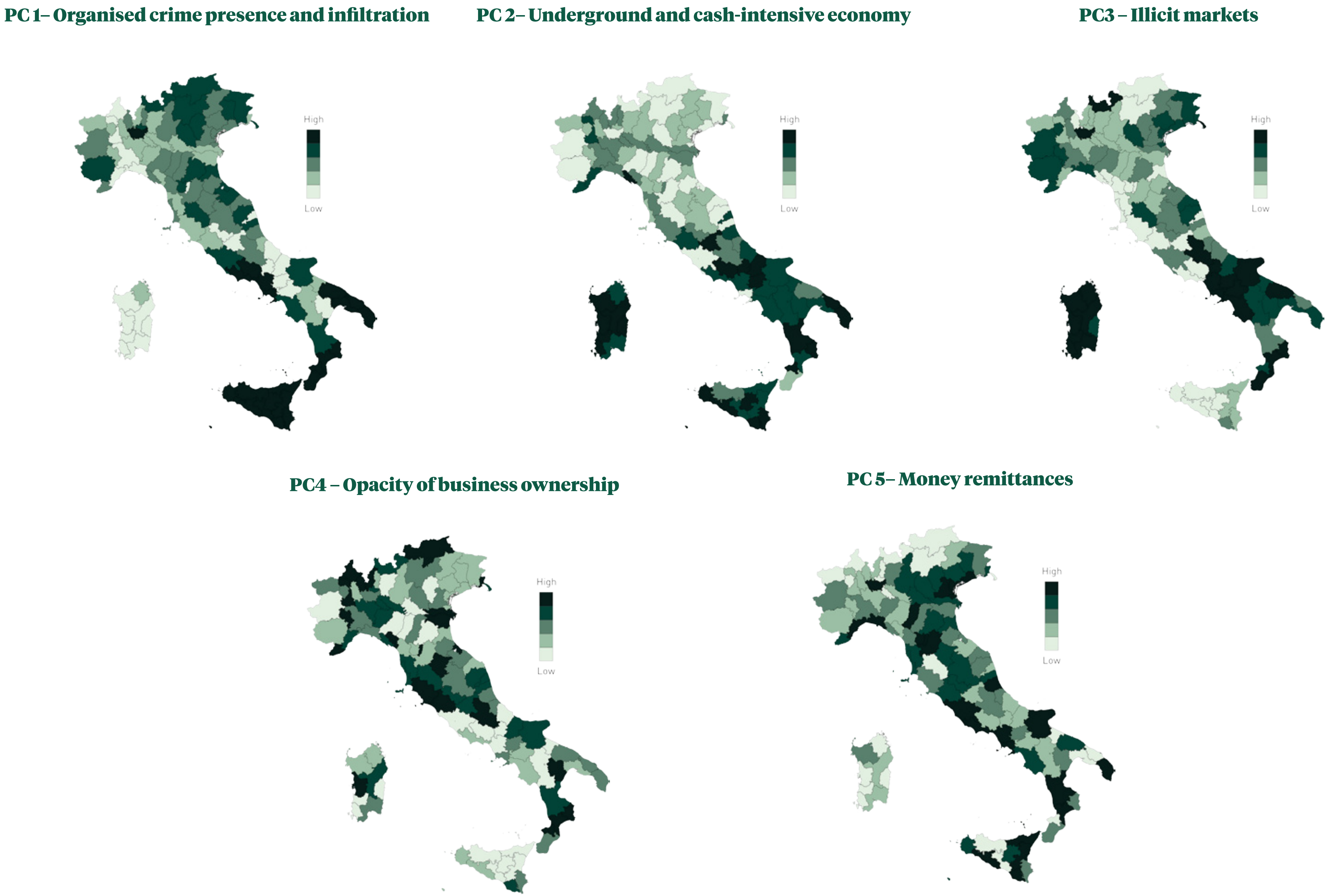
The fourth component, explaining 14% of the variance, captures mainly the effects of the proxies measuring, on the one hand, the **complexity of business ownership structure** (BO distance), and on the other, the volume of **shareholders from risky jurisdictions** (weighted for the average company size, see above). With some exceptions in the South (Vibo Valentia, Catanzaro and Matera) all provinces with highest values of this PC are in the north (e.g. Como, Varese, Verbanio-Cusio-Ossola, Imperia, Alto Adige, Trieste) and usually at the **border with foreign countries**, such as Switzerland, Monaco and Austria which score high in the FSI score.

PC5

Principal component 5 (PC5) – Money remittances

Although explaining a small part of the data variability (8% of the model variance), **money remittances** (as % of provincial GDP) are identified by the PCA as a **separate ML risk component.** As stressed in Part 2, money transfers, besides being the only available measure of (opaque) financial transactions to foreign countries (no data is available on wire transfers), are an area particularly vulnerable to ML due to the difficult controls on money transfer agents as also highlighted by FATF and the Italian MER (FATF, 2010b; CSF, 2014a).
Those areas ranking higher on the money remittances component are the Italian provinces with high concentrations of migrants: **Prato** first of all (due to the large Chinese community) but also Florence, Rome, Naples, Milan. Most of these provinces have been involved in 2010-2013 in the *Qian Liu/Qian* Ba police investigations, which revealed massive illicit financial flows to China through money transfer services (Riccardi, Soriani, et al., 2016, pp. 133–134).

Figure 16 – Principal components of ML risk in Italy



Source: Transcrime – UCSC elaboration

STEP 6 – AGGREGATION AND COMPOSITE INDICATOR CONSTRUCTION

The principal components, identified through the PCA, can be then combined together in order to construct a synthetic composite indicator of ML risk. For this purpose, they are **aggregated using as weight the proportion of variance** (of the model) explained by each component, and then normalised to the **scale 0-100** according to a min-max criterion, where 100 = highest ML risk.[32] In other words (see Annex for details):

$$ML\ RISK\ INDICATOR_i = \sum_{j=1}^{J}(S_{ij} \times w_j) =$$

$$=(S_{1i} \times w_1)+(S_{2i} \times w_2)+(S_{3i} \times w_3)+(S_{4i} \times w_4)+(S_{5i} \times w_5)$$

where the subscript i = 1, ... ,I indicates the province (in our case I = 110), j = 1, … , J the component (J = 5) and wj = proportion of variance (out of the total variance explained by the model) explained by each of the five components. S_{ij} is the relevant value extracted by the PCA for each province and for each component.

The table below presents the top 12 Italian provinces ranked according to the overall ML risk. The **top four are located in Calabria**: they score high in terms of mafia threat (PC1), underground economy and large use of cash (PC2) and illicit markets (PC3). They are followed by **Naples and Caserta** (strong Camorra presence and infiltration, high volumes of illicit markets) and some Sicilian provinces (Agrigento, Palermo, Trapani, Caltanissetta). The first among the provinces not traditionally characterized by mafia presence are Imperia and Prato. **Imperia** ranks first for business ownership opacity, but it is also an area characterized by high levels of cash-use and underground economy and an intense cross-border activity of OC groups ('Ndrangheta in particular), especially because of the proximity with the PACA region in France (see Riccardi & Camerini, 2016). **Prato** is characterised by high cash-intensiveness, high irregular labour, and a high volume of money remittances (first province in Italy in terms of remittances on GDP), all of them mainly related to the presence of Chinese groups active on the boundary between the legitimate and illegal economy.

Table 17 - Top 12 provinces by ML Risk Composite Indicator

Province	Macro region	PC1	PC2	PC3	PC4	PC5	ML Risk Composite Indicator
		OC presence and infiltration	Underground and cash-intensive economy	Illicit markets	Opacity of business ownership	Money Remittances	
Reggio Calabria	South	100	45.2	43.1	14.2	10.4	**100**
Vibo Valentia	South	70	81.5	31.6	36.9	6.9	**94.9**
Catanzaro	South	44.3	78	40.2	60.9	14.1	**85.4**
Crotone	South	35.9	88.8	37	25.4	9.8	**67.1**
Napoli	South	36.4	37.2	100	15.4	21	**66.3**
Imperia	North-west	9.8	70.8	29.3	100	13.4	**62.5**
Caserta	South	29.4	67.8	77.3	8.8	15	**62**
Agrigento	Islands	42.9	99.1	0.7	11.2	13.9	**59.9**
Palermo	Islands	72	56.7	5.7	0	4.5	**59.5**
Caltanissetta	Islands	51.1	70.2	20.7	8.8	6.8	**57.7**
Trapani	Islands	38.5	86.7	9.2	10.1	12.2	**52.3**
Prato	Centre	5.8	66.8	22	27.7	100	**51.1**

Source: Transcrime – UCSC elaboration

32. The choice of using the proportion of variance as weight for components' combination makes it possible to address the weakness of most composite indicators currently available in the literature, i.e. the fact that factors are aggregated attributing discretionary weights which heavily impact on the final result and ranking.

STEP 7 – SENSITIVITY ANALYSIS AND VALIDATION

Is the final ML risk indicator presented above in line with other evidence on ML in Italy? Is it possible that slight variations in the methodology could significantly affect the overall result and change the ML risk ranking of the 110 Italian provinces? To address these questions and **validate the composite indicator**, two tests are carried out.

Correlation between ML risk composite indicator and other ML measures

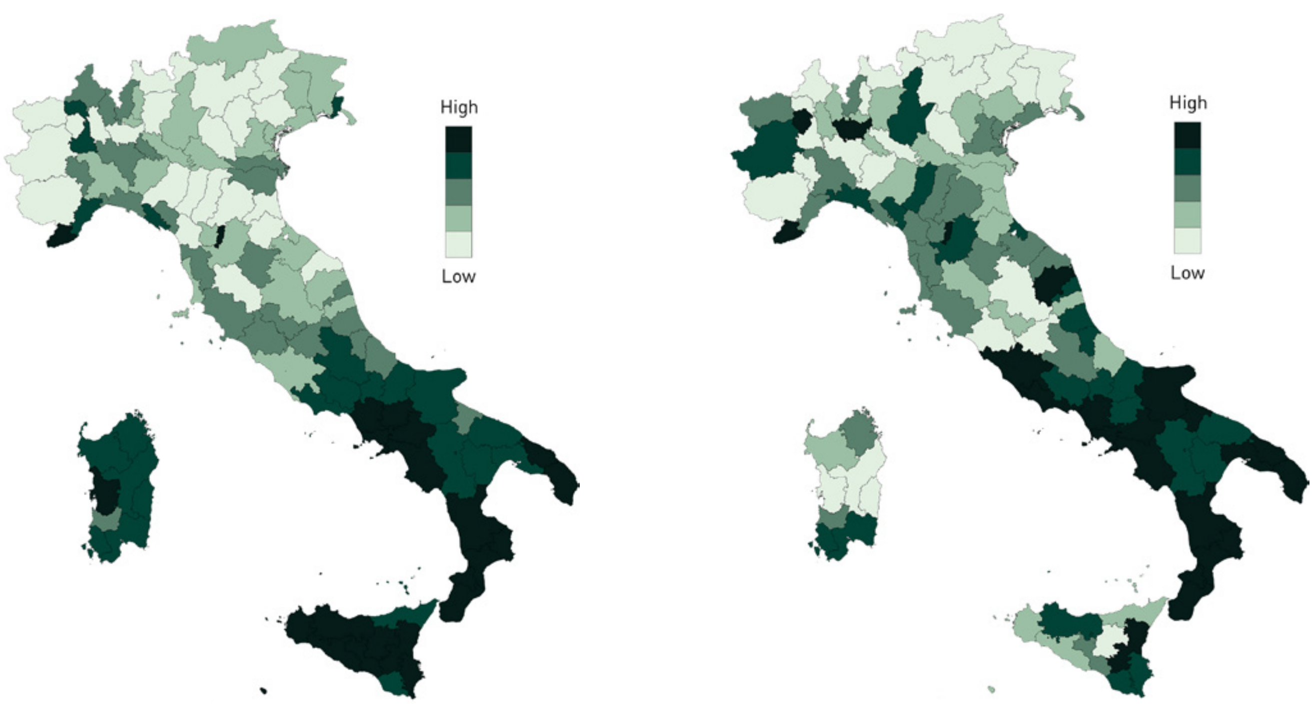
First, the indicator is compared with an alternative measure of money laundering, in this case the number of STRs per bank (average 2012-2014). The two variables are **positively and significantly correlated (Pearson's r = 0.7)**. The ML risk indicator is correlated positively also with the ratio of ML offences to the population, even if to a lesser extent (r = 0.22). The two maps below show the final ML risk composite indicator (left) and the number of STRs per bank agency (right). The similarity between the two maps is evident: the darkest areas in the IARM model are also those with the highest ratios of STRs (e.g. southern Italian provinces, Prato, Imperia).

Sensitivity analysis

Second, a **sensitivity analysis** is performed in order to check if changes in the methodology regarding, for example, the **weighting, aggregation and normalisation** of the variables involved in the PCA do affect the overall result and ranking of ML risk. Table 18 below lists the different methodological options which are tested in the sensitivity analysis (see Annex for details), while the two *corrplots* in Figure 18 present:

- the correlation among the composite indicators' scores resulting from application of the various parameters/options.[33]
- the correlation among the composite indicators scores produced after dropping one selected variable at a time from the final model (Model 1).[34]

Figure 17 - ML risk composite indicator (left) and STRs per bank agency (right)



Source: Transcrime – UCSC elaboration

33. The final model is the VPSTM, which refers to the composite indicator obtained from application of the following options: V = Varimax algorithm is used in the rotation of components in the PCA; P = components are aggregated based on the proportion of variance explained.; T = principal components not normalised; M = final indicator normalised according to min-max criterion. As a matter of example, the option OESDM refers to the composite indicator obtained from the application of the following options: O = Oblimin algorithm is used in the rotation of components in the PCA; E = components are aggregated using equal weights; S = components are aggregated using weighted arithmetic mean; D = components are normalised before being aggregated; M = components and the final indicator are normalised according to min-max criterion (see Dugato et al, 2014).

34. The full nomenclature of all models from Model 1 (final indicator presented) to Model 20 can be found in Annex

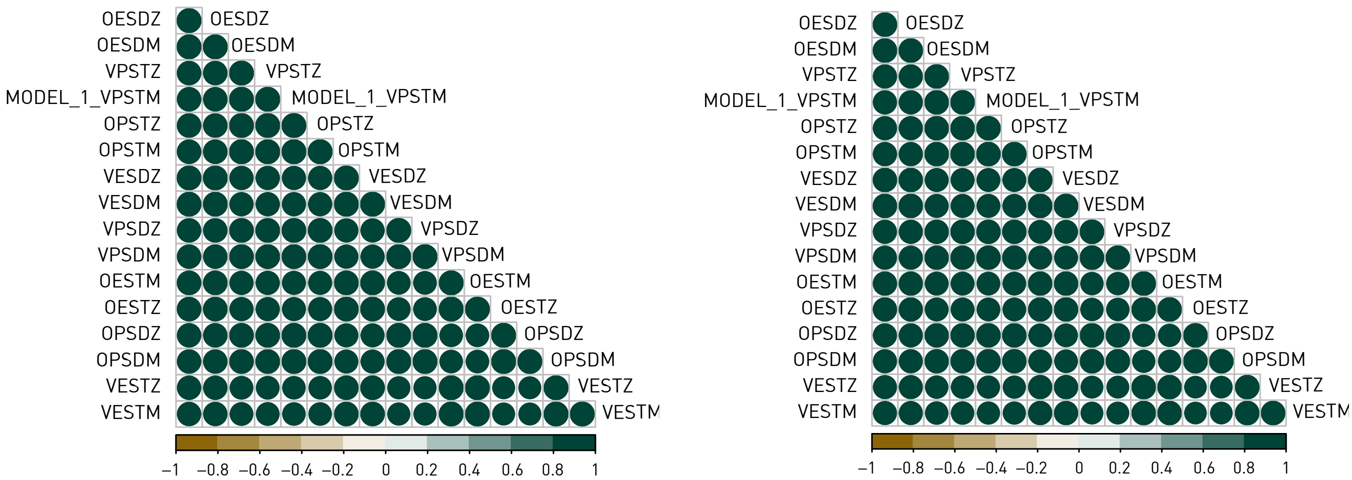
Table 18 - Different parameters adopted to construct the ML risk composite indicator

Highlighted in grey are the options adopted to construct the final indicator (Model 1 - VPSTM)

Step	Methodological options	Label
PCA rotation of components	Varimax	V
	Oblimin	O
Weighting	Weights based on the proportion of variance explained	P
	Equal weights (average score)	E
Aggregation	Weighted arithmetic mean	S
Normalisation method of the components	Standardisation or Z-scores	T
	Min - Max	D
Normalisation method of the final indicator	Standardisation or Z-scores	Z
	Min - Max	M

Source: Transcrime – UCSC elaboration

Figure 18 – Correlation among ML risk composite indicators after applying different methodological options (left) or using different proxy variables (right)



Source – Transcrime – UCSC elaboration

As illustrated by Figure 18, all the scores for the indicators resulting from the different options are **highly correlated (average Pearson's r = 0.97)**, which suggests that changes in the methodology do not significantly affect the overall result and ranking, and that the **IARM ML composite indicator remains solid and robust** even after the sensitivity analysis. Some choices change the rank of certain provinces (e.g. using equal aggregation weights increases the risk of provinces, such as Prato, which have a high volume of remittances as % of GDP), but the overall picture remains the same (see the Annex for the ranking of the 110 provinces according to different methodological choices).

2.3 Analysis at business sector level

The same 7-step methodological approach used to develop a composite indicator at provincial level (Section 2.2) is adopted for an analysis at business sector level. In particular, a **composite indicator of ML risk** is calculated for **77 NACE Rev. 2 divisions** (2-digits).[35]

Developing a composite indicator at business sector level is **even harder** owing to the difficulties of identifying and operationalising risk factors, and to very limited data availability. Presented below is an **exploratory analysis** – the first of this kind performed in the literature – which represents only the first step for further investigation.

STEP 1 – ML RISK FACTORS IDENTIFICATION

As in the analysis at area level, ML RF across Italian business sectors are identified on the basis of a **review of the academic literature, institutional reports, investigative and judicial evidence**, and then validated by means of interviews with experts. The RF identified are classified according to the FATF taxonomy (*Threats, Vulnerabilities and Consequences* – see Chapter 1) (Dawe, 2013; FATF, 2013a), and grouped into a **tree-structure** (*risk factors, risk sub-dimensions*) (see Figure 19 below).

As mentioned in Chapter 1, the previous **literature is scanty** and focuses more on risks across territories than across economic sectors. Some of the RF categories identified for the provincial analysis are **not applicable at industry level** (e.g. illicit markets). As a result, the following RF are identified:

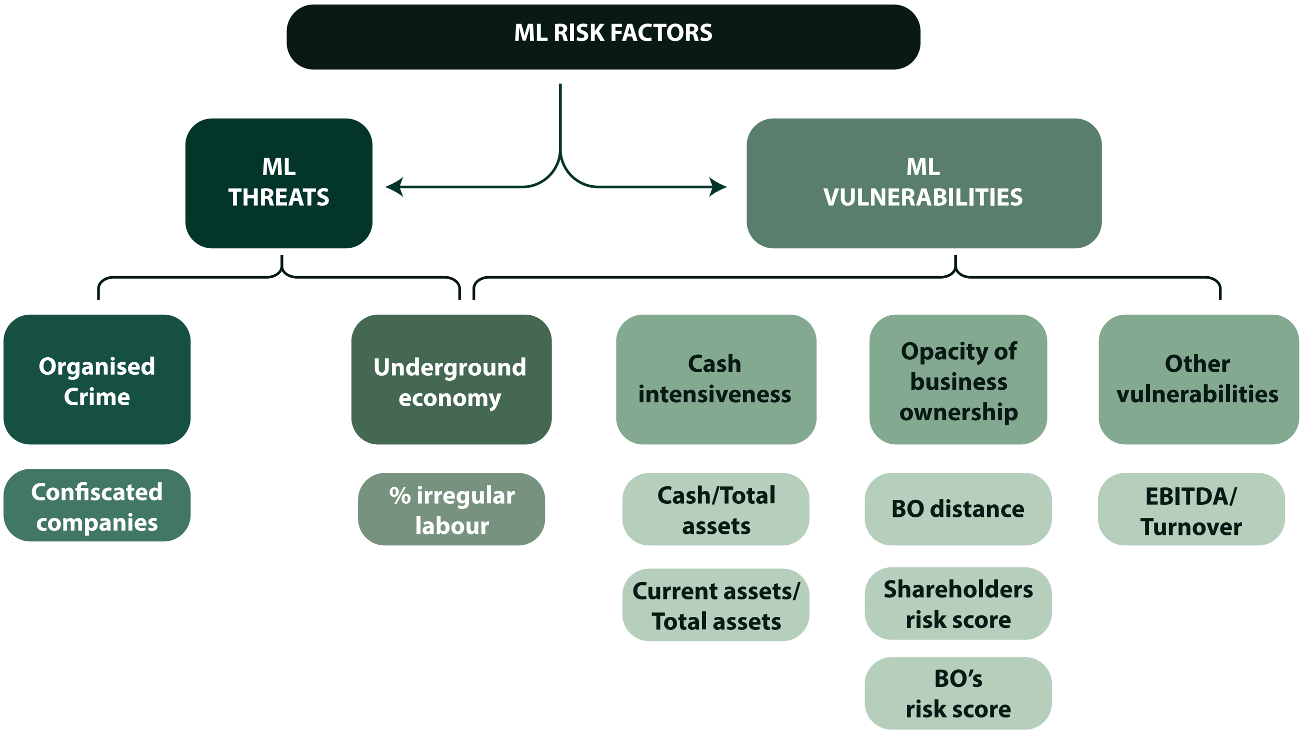
- OC infiltration (Threat)
- Tax evasion & Underground economy (Threat/ Vulnerability)
- Cash-intensiveness (Vulnerability)
- Opacity of business ownership (Vulnerability)
- Business profitability (Vulnerability)

STEP 2 – ML RISK FACTORS OPERATIONALISATION

Each RF is then *operationalised* into one or more proxy variables in order to enable their measurement and analysis. The proxies are illustrated in the chart and tables below. As said, data available at business sector level are **even fewer than at area level**. Depending on company law requirements in each country, some information (e.g. financial or ownership data) can be found on individual firms but it is not always possible to access and aggregate it at industry level. Other information, like data on the tax gap, is not available in Italy at either NACE section or division level, at least for the purpose of this study. These difficulties translate into a lower number of variables available for use in the PCA.

35. NACE Rev.2 is the statistical classification of economic activities in the European community, adopted in 2007. NACE uses different hierarchical levels. Level 1 (or 1-digit) identifies 21 sections by alphabetical letters (A to U); Level 2 (or 2-digits) identifies 88 divisions by two-digit numerical codes (01 to 99) (see for details http://ec.europa.eu/eurostat/ramon/nomenclatures/index.cfm?TargetUrl=LST_NOM_DTL&StrNom=NACE_REV2&StrLanguageCode=EN&IntPcKey=&StrLayoutCode=HIERARCHIC). The composite indicator is computed at the division level, but this chapter also presents some analyses and descriptive statistics for NACE sections. The section labels used in charts slightly differ from the official NACE classification so that they are more readable. Moreover, sections O, T and U have been excluded from the analysis because there are fewer than 500 registered companies in those business sectors in Italy. Consequently, statistics are presented for 18 sections and the composite indicator is computed for only 77 NACE divisions. For details see the Annex.

Figure 19 - ML risk factors and proxy variables at business sector level in Italy



Source: Transcrime – UCSC elaboration

Money laundering threats

The available data allow coverage of only **two ML threats**: infiltration by organised crime, and tax evasion/underground economy.

Table 19 - List of ML threats proxy variables at business sector level

ML Risk factor	ML Risk sub-dimension	Proxy variable	Variable labels	Source	Disaggrega-tion level	ML Risk dimen-sion
Organised Crime (OC)	OC infiltration	Seized and confiscated companies/ Registered companies	*CONFISCATED_ COMPANIES*	ANBSC	NACE Rev.2 Divisions and Sections	1984-2015
Tax Evasion & Underground economy	Tax evasion	*No data available at NACE Rev.2 classification level (sections – divisions)*				
	Irregular labour	% Irregular working units	*IRREGULAR_ LABOUR*	ISTAT	NACE Rev.2 Sections[36]	2001-2013

Source: Transcrime – UCSC elaboration

36. Data on irregular labour are available at NACE rev.2 Division level only for Section C – Manufacturing, while for the other business sectors they can be found only at the section level.

Organised crime

OC infiltration in business sectors focuses on Italian mafias, and it is again measured as the ratio between the **number of companies seized from mafia groups** in Italy and the number of registered companies.[37] Other proxies adopted in the provincial analysis to measure mafia infiltration and presence (e.g. mafia homicides, dissolution of city councils, etc. – see 2.2) are not applicable to business sectors. The underlying hypothesis is that, ceteris paribus, the higher the degree of infiltration, the greater the risk of ML in the same sector.

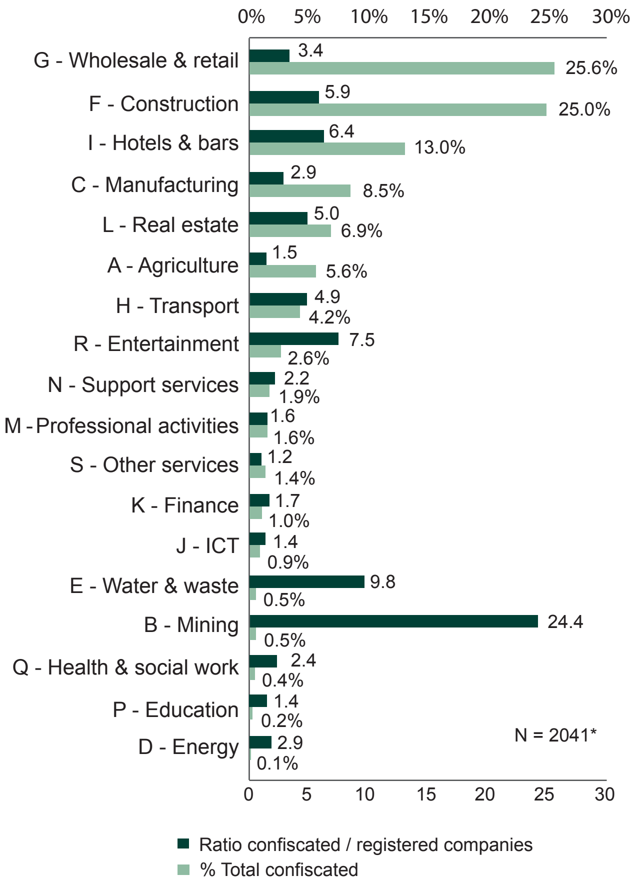
According to available data provided by ANBSC, about 3,500 companies have been seized by Italian authorities since 1984, and 2,500 of them were eventually confiscated. Most of them concentrate in the wholesale and retail trade sector (NACE section G) and construction industry (section F). The sections with the highest ratios between confiscated and registered companies are **mining and quarrying, water and waste management, construction, entertainment and accommodation** (respectively NACE sections B, E, F, R, I) (Figure 20).

As noted in previous studies, the first three sectors (B, E, F) are characterised by high **public expenditure and public procurement**, and they allow mafia groups to benefit from their connections within the political elite and public administration (Sacco, 2010; Transcrime, 2013). In particular, mining (e.g. sand mines and pits), plays a crucial role because it is the first link in the construction industry/cement cycle (of key importance in the mafia economy), but also because it is used for illegal waste disposal – sand mines and quarries are ideal for hiding illegal waste (D'Amato, Mazzanti, & Nicolli, 2015; Legambiente, 2016; Riccardi, 2014).

Bars, restaurants, hotels (Section I) are also widely exploited by criminal organisations for laundering purposes because of their **cash-intensive, labour-intensive and low-tech** nature (Transcrime, 2013; Riccardi, Soriani, et al., 2016; Fondazione Res, 2014; Fantò, 1999). **Gambling and betting** (Section R) have historically attracted the interest of organised crime, but in recent years in Italy they have further developed with the spread of video-lottery terminals (VLT), slot-machines, and recreation rooms (DIA, 2015; DNA, 2014; Cantone & Di Feo, 2014; Poto, 2012; Busa & La Rocca, 2011).

At the NACE division level, those with highest number of confiscated companies are **construction of buildings (F 41), retail trade (G 47), bars and restaurants (I 56)**. In terms of ratio with registered businesses, ranking highest are divisions related to the extraction of sand, production of cement, and building industry (B 08, C 19, C 23, F 41), waste management (E 38), gambling and betting (R 92) and broadcasting (J60).

Figure 20 - Companies confiscated from mafia-type OC by sector (NACE divisions)
1984-2015. % of total and ratio to 10,000 registered companies. NACE 2007 Sections excluding O, T, U



Source: Transcrime – UCSC elaboration of ANBSC data

**Out of the total number of 3447 confiscated companies, for 1406 information on business sector is not available*

37. In this case, data are available on companies finally confiscated in the period 1984-2015 and seized from 2013 to 2015. It has been decided to include also seized companies in order to ensure the better representativeness of those sectors, which have seen large numbers of infiltration cases in recent years but have been targeted by confiscation measures only recently (e.g. VLT, gambling, betting agencies).

Table 20 – Companies confiscated from mafia-type OC by sector (NACE divisions)
First 7 NACE divisions by number and ratio. 1984-2015

Rank	Number confiscated companies	Ratio confiscated/registered companies
1	F 41 – Construction of buildings	C 19 – Manufacture of coke and refined petroleum products
2	G 47 – Retail trade, except for motor vehicles and motorcycles	B 08 – Other mining and quarrying
3	I 56 – Food and beverage service activities	C 23 – Manufacture of other non-metallic mineral products
4	G 46 – Wholesale trade, except for motor vehicles and motorcycles	R 92 – Gambling and betting activities
5	L 68 – Real estate activities	J 60 – Programming and broadcasting activities
6	A 01 – Crop and animal production, hunting and related service activities	E 38 – Waste collection, treatment and disposal activities; materials recovery
7	F 43 – Specialised construction activities	F 41 – Construction of buildings

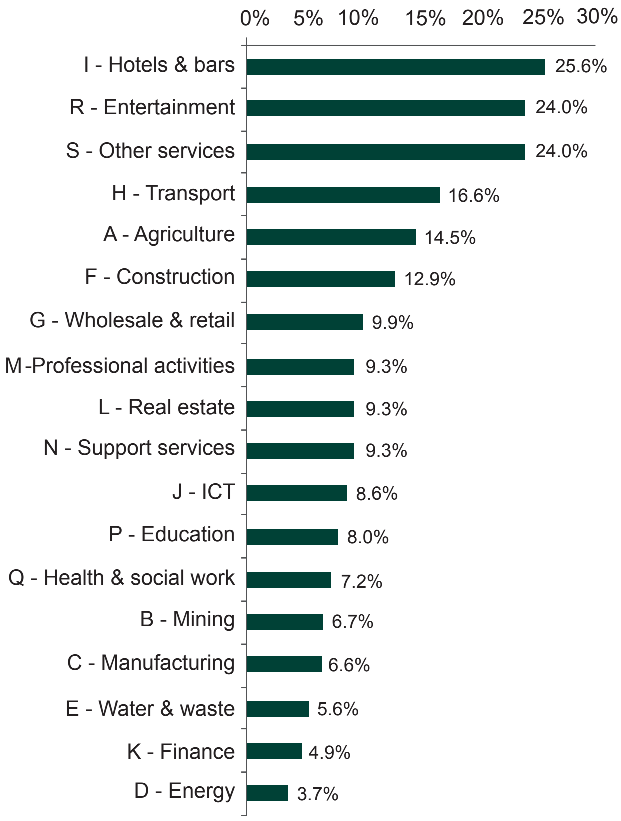
Source: Transcrime – UCSC elaboration of ANBSC data

Tax evasion and underground economy

Economic sectors characterised by high levels of **tax evasion** are often those where it is more likely that illicit proceeds are generated but also laundered (Schneider, Raczkowski, & Mróz, 2015; Tavares, 2013). Unfortunately, measures on corporate tax evasion at business sector level are not available for the purpose of this study. The only available data is the % **of irregular labour** over the total workforce per sector, which is also related to tax evasion, in particular to labour taxes and contributions.[38] The selection of this variable is also justified by the fact that **black salaries are a well acknowledged laundering method**, especially in certain areas and economic activities (Williams & Schneider, 2013; Schneider, 2012; Dell'Anno, Gomez-Antonio & Pardo, 2007).

On average, ISTAT estimates that **4% of workers** in Italy are irregular (average 2001-2013), a percentage which has been increasing in recent years due to the economic crisis (ISTAT, 2016a). NACE sections I (Food and accommodation), R (Entertainment), S (Other service activities), H (Transportation and storage), A (Agriculture, forest and fishing), F (Construction) record the highest levels. In particular, more than one-fourth of total workers in bars, restaurants and hotels are estimated to be irregular (Figure 21).

Figure 21 - % of Irregular labour on total working units by NACE business sector
Average 2001-2013. NACE Sections excluding O, T, U



Source: Transcrime – UCSC elaboration of ISTAT data

38. See paragraph 2.2 and (EUROSTAT, 2015) for a definition of underground economy. Data on irregular labour are available only at NACE section level, except for manufacturing (Section C) where details at division level are provided.

Money laundering vulnerabilities

ML vulnerabilities at business sector level are identified by mirroring those at area level. However, in this case the **operationalisation is harder** because of the lack of previous literature in the ML field. Proxies are developed by looking at other domains, such as accounting, corporate finance or corporate governance. For all three of the vulnerabilities identified, data are collected from the **Bureau van Dijk** ORBIS database, which provides **ownership and financial information at individual company level**, and they are then aggregated by economic sector.[39]

Table 21 – List of ML-vulnerabilities proxy and control variables at business sector level

ML Risk factors	ML Risk sub-dimension	Proxy variables	Variable labels	Source	Disaggregation level	Covered years
Cash intensiveness	Cash-intensive nature of businesses	Cash / Total Assets	*CASH_ ASSETS*	Transcrime - UCSC elaboration on BVD data	NACE Rev.2 Divisions	Last available year
		Current assets / Total assets	*CURRENT_ ASSETS*	Transcrime - UCSC elaboration on BVD data	NACE Rev.2 Divisions	Last available year
Opacity of business ownership	Opacity business ownership structure	BO distance	*BO_DISTANCE* *BO_DISTANCE_w**	Transcrime - UCSC elaboration on BVD data	NACE Rev.2 Divisions	Last available year
	Ownership links with risky jurisdictions	Shareholders' risk score	*RISKY_SHAREHOLDERS* *RISKY_SHAREHOLDERS_w**	Transcrime - UCSC elaboration on BVD and TJN data	NACE Rev.2 Divisions	Last available year
		BOs' risk score	*RISKY_BO* *RISKY_BO_w**	Transcrime - UCSC elaboration on BVD and TJN data	NACE Rev.2 Divisions	Last available year
Business profitability	Business profitability	EBITDA / Turnover	*PROFIT*	Transcrime - UCSC elaboration on BVD data	NACE Rev.2 Divisions	Last available year
Control variables						
Company size		Employees / Companies	*EMPLOYEES_ AVERAGE*	Transcrime - UCSC elaboration on BVD data	NACE Rev.2 Divisions	Last available year
		Assets / Companies	*ASSETS_ AVERAGE*	Transcrime - UCSC elaboration on BVD data	NACE Rev.2 Divisions	Last available year
		Turnover / Companies	*TURNOVER_ AVERAGE*	Transcrime - UCSC elaboration on BVD data	NACE Rev.2 Divisions	Last available year
		Registered Companies	*NUM_COMPANIES*	Infocamere	NACE Rev.2 Divisions	2014

Source: Transcrime – UCSC elaboration

** Variables ending with "w" are weighted for the average company size in the business sector as a proxy for the presence of multinational companies (see below and Methodological Annex for details)*

39. As mentioned in section 2.2 on the analysis at area level, although the Bureau van Dijk (BvD) ORBIS database covers almost the entire universe of the 6 million Italian companies, financial and ownership information is available only for a subset of respectively 3,527,143 and 3,669,902 companies, i.e. those legal forms (like limited companies) which are required to file this information with the business registry. See the Annex for details.

Cash-intensiveness

As stressed in Chapter 1, **cash-intensive businesses** ease the concealment and integration of illicit proceeds in the legitimate economy and are therefore helpful for money laundering purposes (FATF, 2010a; Riccardi & Levi, 2017; Gilmour & Ridley, 2015; Gilmour, 2014; Transcrime, 2013). But measuring the level of cash intensity at economic sector level is not easy. One option is to consider the extent to which two companies in a certain sector detain assets in cash or liquidity, and therefore to measure:

- the average **cash/total assets** ratio of the companies operating in a certain sector;
- the average **current assets/total assets** ratio, which with respect to the previous one also takes into account trade receivables, inventory, and other current assets.[40]

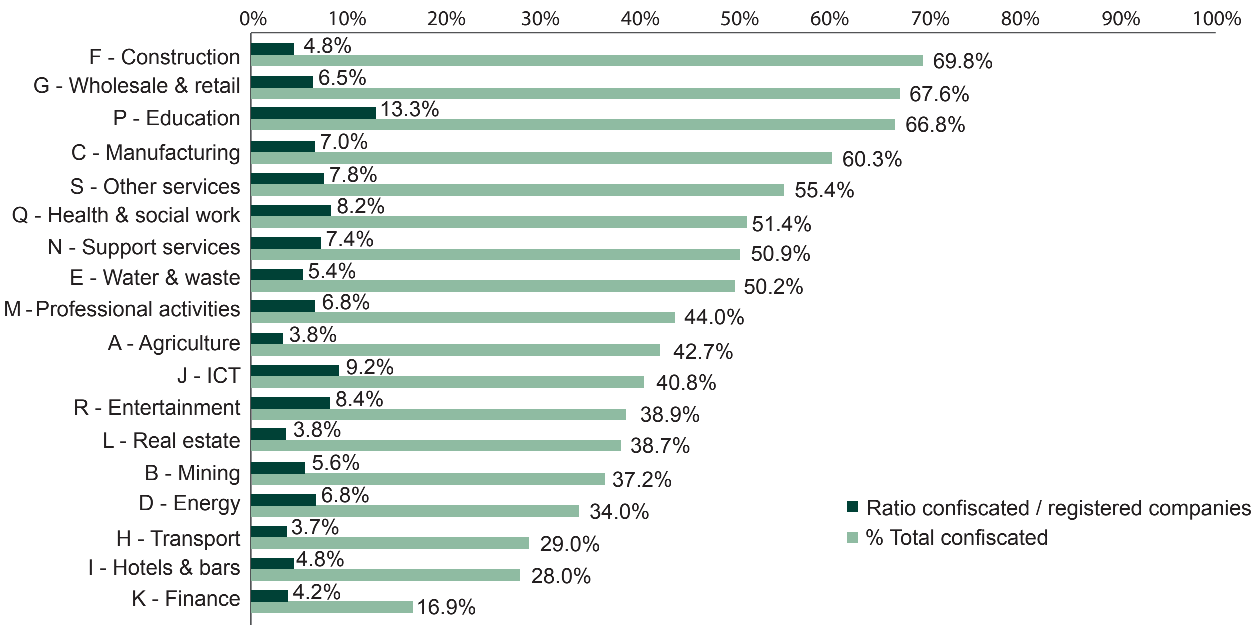
There is a large amount of empirical evidence that companies involved in money-laundering schemes (especially those related to mafia infiltration) register not only higher liquidity but also higher levels of current assets, which may be easy to manipulate from an accounting point of view and may conceal illicit inflows/outflows (see e.g. Di Bono et al, 2015; Transcrime, 2013).

The figure below shows that, as expected, sectors **F (Construction) and G (Wholesale and retail trade)** are those with the highest levels of current assets in the total. More surprisingly, sectors P (Education) and C (Manufacturing) also show high ratios. In particular, P is the sector with the largest share of cash in total assets, followed by Section J (Information and communication), R (Arts, entertainment and recreation) and Q (Health and social work activities) Section R (Arts, entertainment and recreation) includes very high cash-intensive businesses, such as gambling and betting activities (R 92), gaming rooms or night clubs (R 93).

The disaggregation at NACE division level shows more heterogeneous patterns. In terms of current assets/total assets ratio, those divisions with the highest levels are **S 95** (Repair of computer and household goods), **M 73** (advertising and market research) and two sectors related to the construction industry, namely **N 81** (services to buildings and landscape activities) and **F 43** (specialised construction), all of which, on average, have more that 75% of the total assets detained in current assets. Also other divisions of the building industry record ratios higher than 70%. In terms of cash/total assets, J 59 (TV and video production) is followed by E 39 (waste & remediation), R 90 (creative, arts and entertainment) and S 94 (Activities of membership organisations).

Figure 22 – Cash & Current assets. Average % on total assets

NACE Sections excluding O, T, U. Last available year



Source: Transcrime – UCSC elaboration of BvD data

40. These proxies have been preferred to other fundamental analysis ratios due to greater data availability. Other measures of liquidity are, for example, receivables days (or debtors days) which measure the average length of time taken by a company's customers to pay their debts (O'Regan, 2006, p. 223). It can be assumed that the lower the receivables days, the more liquid the payments received by a company. Unfortunately, details on debtors and payables are not largely available in the source used for analysis, so that this ratio cannot be calculated in a systematic way.

Opacity of business ownership

As in the analysis at area level, the complexity of corporate structures at industry level is analysed with respect to two sub-dimensions:

- **The level of complexity** of businesses' ownership structure as such;
- The volume of business ownership connections with shareholders and BOs from **risky jurisdictions**;

Complexity of business ownership structure

The proxy for the first dimension is the so-called **BO distance**, which has been already used for the analysis across provinces and measures the average number of 'steps' separating a company from its beneficial owner(s).[41] The higher the BO distance, the more complex the ownership structure, and the greater the ML risk.

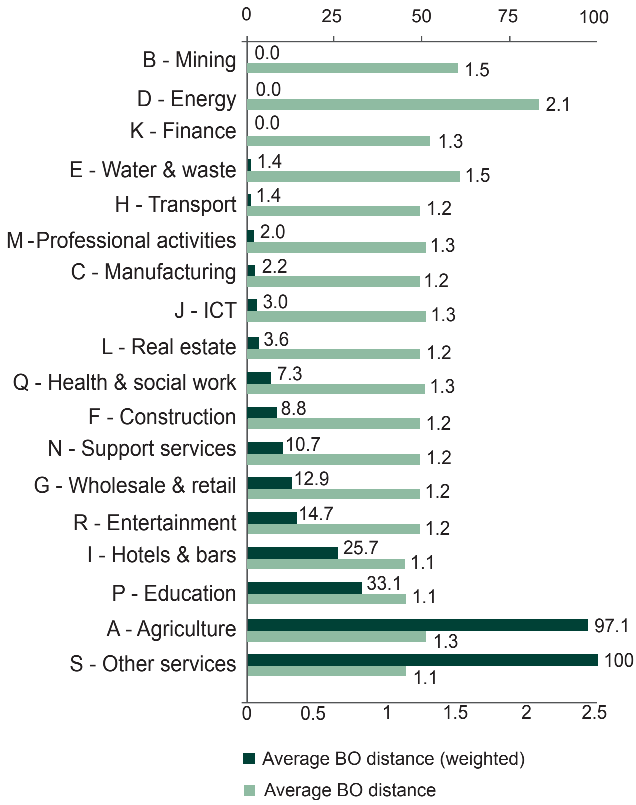
Electricity, water supply and waste management, the financial industry, and mining and quarrying (respectively **NACE sections D, E, K and B**) are characterized by higher BO distance. This may be due to the larger number of **multinational companies** operating in those industries. The divisions with the highest BO distance are, in particular, D 35 (Electricity, gas, steam and air conditioning supply, with on average 2.1 steps between companies and their beneficial owner(s)), E 36 and E 37 (Water supply and sewerage, with respectively 1.9 and 1.8), K 65 (Insurance, 1.9) and C 21 (pharmaceuticals).

However, in order to identify the actual anomalies and control for the presence of multinational enterprises, the BO distance in each business sector is weighted by the average company size in the sector (as done in the analysis at provincial level - see 2.2 and Annex for details). In this scenario, **sections S (Other services), A (Agriculture), P (Education)** and **I (Bars, restaurants and hotels)** rank highest.

41. See footnote 24

Figure 23 – Average BO distance per business sector

Average distance and average distance weighted by average company size (scale 0-100). Excluding NACE sections O, T, U

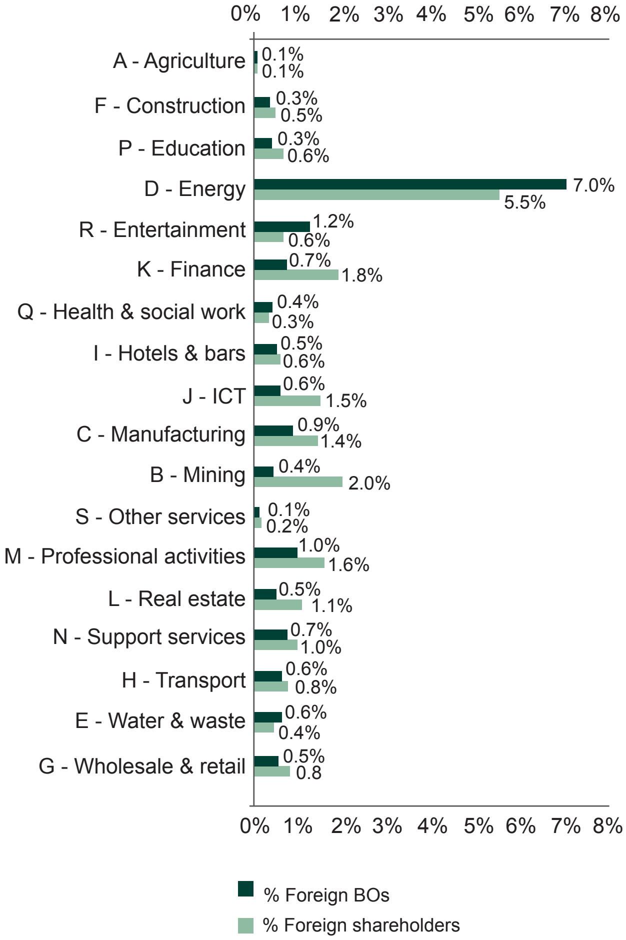


Source: Transcrime – UCSC elaboration of BvD data

Business ownership connections with risky jurisdictions

At **business sector level**, the industries with the highest percentages of **foreign shareholders** are, again, those with the largest number of multinational companies and volume of FDI: energy (section D), financial companies (K), mining (B) and some manufacturing sectors, such as pharmaceuticals (C 21) and oil & gas (C 19). The sectors with the highest percentages of **foreign BOs** are almost the same as shareholders, with the exception of R 92 (gambling and betting activities): a result which would require further investigation given the abundant evidence of OC infiltration of this industry in recent years.

Figure 24 – Foreign shareholders and foreign BOs. % on total shareholders and BOs per sector
NACE sections, excluding O, T, U



Source: Transcrime – UCSC elaboration of BvD data

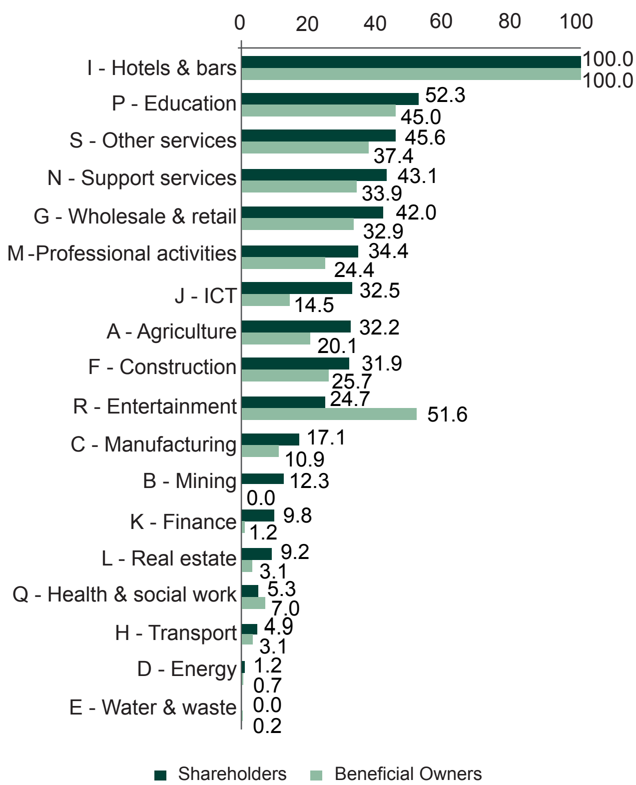
However, as said, not all foreign nationalities encompass the same ML risk. As in the analysis at area level, it is necessary to calculate the volume of business ownership **connections with 'risky' jurisdictions**. The same methodology is adopted here, i.e. the % of foreign shareholders and BOs per each nationality in each business sector is multiplied by the relevant value of the **FSS - Financial Secrecy Score** (Tax Justice Network, 2015b).[42] The value is then weighted by a measure of company size (in this case, the average total assets) in order to offset the incidence of multinational companies (see Annex).

42. As described earlier, the Financial Secrecy Score (FSS) is a composite indicator which condenses into a national score different dimensions of secrecy related to: A) access to beneficial ownership information; B) corporate transparency; C) efficiency of tax and financial regulation; D) compliance with international standards; E) international cooperation (Tax Justice Network, 2015). For further detailed see Annex.

At NACE section level, after controlling for company size, **bars, restaurants and hotels (I), education (P), other services (S)** record the highest value with respect to shareholders from "risky" jurisdictions. Bars, restaurants, hotels rank first also with respect to beneficial owners, where **section R (entertainment)** scores second (Figure 25).

At the **NACE division level**, I 56 (Food and beverage service activities) is the division with the highest value for both Shareholders and BOs. Divisions S 95 (Repair of computers and personal and household goods) and M 74 (Other professional, scientific and technical activities) also present a high score for the shareholder indicator while controlling for the average company size within the sector, while N 79 (Travel agency, tour operator reservation service and related activities) and R 92 (Gambling and betting activities) score high in relation to risky BOs.

Figure 25 – Business ownership connections with risky jurisdictions (NACE sections)
Scale 0-100 (100 = highest risk). Weighted by sector's average company size. Excluding sections O,T,U. Last available year



Source: Transcrime – UCSC elaboration of BvD and TJN data

Figure 26 – Business ownership connections with risky jurisdictions (NACE divisions)

First 5 NACE divisions. Last available year

Rank	Shareholders' risk score	Beneficial owners' risk score
1	I 56. Food and beverage service activities	I 56. Food and beverage service activities
2	S 95. Repair of computers and personal and household goods	N 79. Travel agency, tour operator reservation service and related activities
3	M 74. Other professional, scientific and technical activities	R 92. Gambling and betting activities
4	N 79. Travel agency, tour operator reservation service and related activities	M 74. Other professional, scientific and technical activities
5	M 73. Advertising and market research	P 85. Education

Source: Transcrime – UCSC elaboration of BvD and TJN data

Business profitability

This is operationalised through a measure of **gross profitability**, namely the EBITDA/Turnover ratio (O'Regan, 2006). Some literature stresses the role that business profitability may have in **attracting investments by criminal organisations** and **therefore money laundering** activities (Kruisbergen et al., 2015; Masciandaro et al., 2007, p. 7; Unger & Rawlings, 2008; Williams, 2001). For example, it has been noted that mafia groups in Italy have in recent years infiltrated companies active in the renewable energy sector – especially windpower – characterized by high subsidies and increasing profits (Caneppele, Riccardi & Standridge, 2014) or the VLT and gaming industry, which is growing rapidly (Poto, 2012; Riccardi, Milani,et al., 2016).

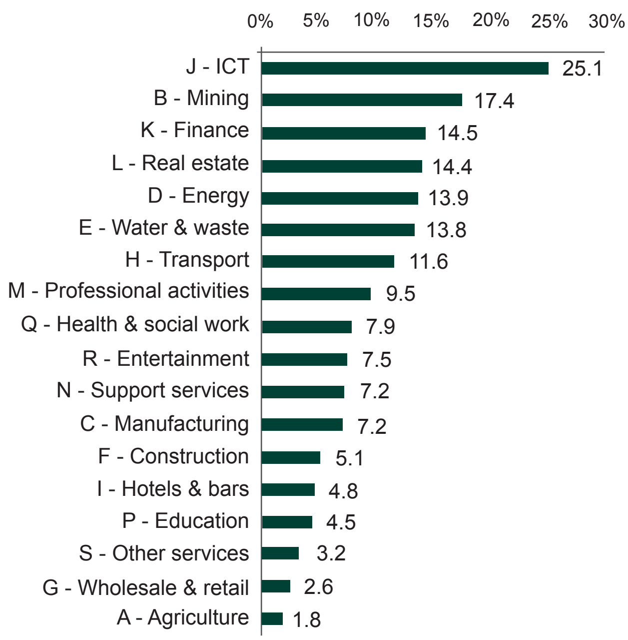
However, some other empirical research shows that **no clear correlation** can be found between the level of criminal infiltration and business sector profitability in Italy (Riccardi, 2014; Donato et al, 2013; Transcrime, 2013): mafia groups are rent-seeking rather than profit-maximising organisations and aim at increasing, not economic profit, but utility in a broader sense – power, control of the territory, social consensus (Riccardi, Soriani et al., 2016, p. 121).

And, moreover, analysis of financial information from the income statement may be strongly affected by accounting manipulations (Di Bono et al, 2015).

For this reason, two models are presented in the PCA analysis: one including the profitability proxy, and one excluding this risk factor.

Figure 27 – Business gross profitability

Average % EBITDA margin by NACE section, excluding O, T, U. Last available year



Source: Transcrime – UCSC elaboration of BvD data

43. EBITDA stands for "Earnings before interests, taxes, depreciation and amortization", and represents the gross profit after subtracting operational costs from revenues (O'Regan, 2016). High EBITDA margins mean that companies are able to generate high revenues and minimize operational expenses such as personnel costs, costs for services and materials. A measure of gross profitability is preferred than measures of net profitability (e.g. profit margin) in order to minimize the influence of different financial management and tax management strategies across businesses and sectors.

STEP 3 – DATA COLLECTION AND NORMALISATION

As said, data are collected at NACE section (1-digit), division (2-digits) or at the individual company level and then aggregated by business sector (e.g. in the case of financial and ownership information). The sources used are:

- Database provided by **ANBSC – Agenzia Nazionale Beni Sequestrati and Confiscati,** for data on seized and confiscated companies;
- **ISTAT**, for data on irregular labour;
- **Bureau van Dijk ORBIS**, for ownership and financial information. In particular two datasets are used: one for financial data (useful for computing cash-intensiveness and profitability proxies, covering 3.5 million companies) and one for shareholders and beneficial owners (covering 3.7 million companies, 5 million shareholders and 4.5 million BOs).

Time coverage varies depending on data availability. Data available for multiple years (e.g. ISTAT data on irregular labour – 2001 to 2013; and ANBSC data on confiscated companies – 1984 to 2015) are averaged. For BvD information, the last available year is considered. As a result of the data collection, **two datasets are produced**, respectively on the 21 NACE sections and 88 NACE divisions. In order to avoid biases deriving from the low number of businesses, the analysis has considered only those sections and divisions with **more than 500 registered companies**. As a result, the analysis covers **18 NACE sections** (i.e. excluding sections O, T and U) and **77 NACE divisions** (excluding divisions B 05, B 06, B 07, B 09, C 12, H 51, M 75, O 84, T 97, T 98 and U 99).

STEP 4 – DATA EXPLORATION AND CORRELATION ANALYSIS

Once the data are collected, they are analysed through descriptive statistics and inference tests. The corrplot below presents the **linear Pearson correlation** among the proxies identified and other control variables on company size (number of employees, revenues and total assets per company) at the NACE division level (77 NACE divisions).

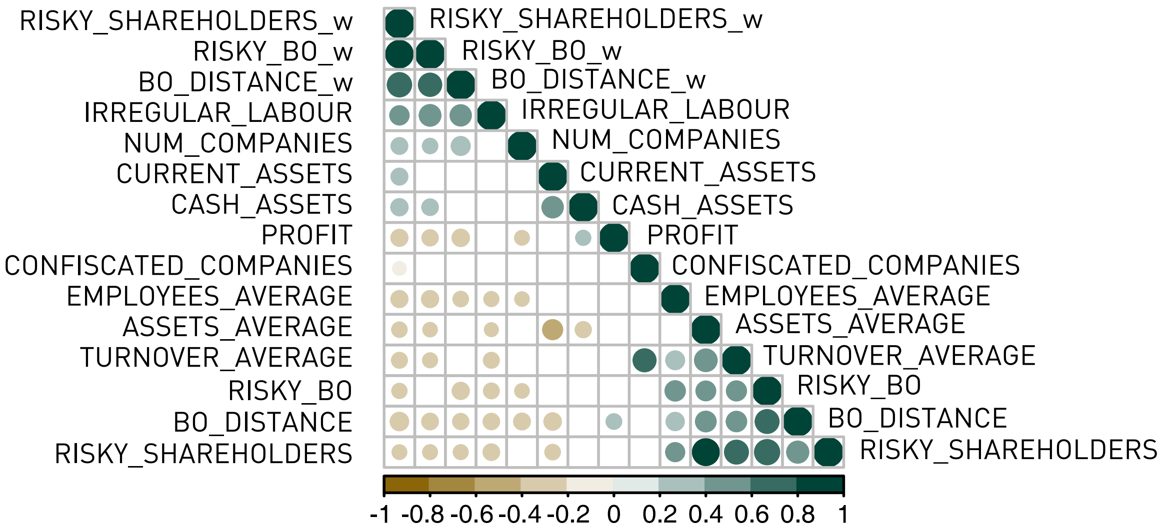
Mafia infiltration (*CONFISCATED_COMPANIES*) is positively correlated with **measures of turnover**. As pointed out by MONEYVAL, "*OCGs invest the proceeds in preferred economic sectors with high turnover as OCG assets can be laundered through high value transactions consistent with the relevant business; for example the construction and real estate sectors*" (MONEYVAL, 2015, p. 20). Despite evidence from the literature and case studies, no correlation could be found between OC infiltration and **irregular labour** (but this proxy is available only at the NACE section level – it would be interesting to repeat the analysis with higher disaggregation detail).

On the other hand, irregular labour is **negatively correlated with company size** variables (e.g. employees per company). This is consistent with the literature highlighting that "*very small firms offer larger room for underground work*" (De Gregorio & Giordano, 2015, p. 16).

The measures of the **opacity of business ownership** (i.e. *BO_DISTANCE, RISKY_SHAREHOLDERS AND RISKY_BOs*) are, as expected, positively correlated with measures of company size: industries with bigger companies at a higher capitalisation are also those with the highest number of foreign shareholders and multinational corporate schemes. However, when **weighted by company size**, the correlation becomes negative, while positive becomes the correlation with **irregular labour** and with measures of **cash intensiveness** (*CASH_ASSETS and CURRENT_ASSETS*).

Future analysis would certainly benefit from the inclusion of further proxies (e.g. tax gap, receivable days) and from the adoption of a higher disaggregation level.

Figure 28 – Pearson correlation among identified proxy variables at business sector level in Italy



Source: Transcrime – UCSC elaboration

STEP 5 - PRINCIPAL COMPONENT ANALYSIS (PCA)

As in the analysis across provinces, the approach adopted to downsize the variety of risk factors into a single composite indicator at the business sector level is the **PCA – Principal component analysis** (see 2.2). The PCA is here performed on the 77 NACE divisions. **7 variables are included** (see Table 22 below). Variables used as controls (e.g. average employees, total assets and revenues per company) are excluded. As regards the proxies for business opacity, those weighted by company size are taken.

A **second model, with 6 variables** (excluding business profitability – i.e. Model 2) is also developed and a second risk score is produced. They are both presented in table 24 and table 25.

According to generally accepted criteria (eigenvalues >=1, each component >10% of the overall variance and cumulative variance >60%), the PCA identifies **four components** which capture more than 84% of the overall data variance. The results support, with empirical evidence, the system of ML risk factors, dimensions and sub-dimensions discussed in previous sections.

Table 22 – Principal component analysis. Matrix of rotated components
Model including business profitability. Varimax rotation

Variables	PC1	PC2	PC3	PC4
RISKY_BO_w	0.89	0.24	-0.11	0.00
RISKY_SHAREHOLDERS_w	0.85	0.34	-0.17	-0.10
BO_DISTANCE_w	0.80	0.02	-0.25	-0.10
IRREGULAR_LABOUR	0.79	-0.24	0.11	0.00
CURRENT_ASSETS	0.00	0.89	-0.23	-0.12
CASH_ASSETS	0.21	0.79	0.45	0.06
PROFIT	-0.24	-0.02	0.91	-0.02
CONFISCATED_COMPANIES	-0.08	-0.06	-0.01	0.99
SS loadings	3.2	1.5	1.1	1.0
Proportion Var.	39.77	19.29	13.18	12.08
Cumulative Var.	39.77	59.05	72.23	84.31
Proportion Explained	0.47	0.23	0.16	0.14
Cumulative Proportion	0.47	0.70	0.86	1.00

Source: Transcrime – UCSC elaboration

Principal component 1 (PC1) – Opacity and irregular labour

The first component accounts for most of the variability in the model (47%), and it is strongly associated with proxies for **business ownership opacity and with the volume of irregular labourers**. When extracting the scores for this component, the divisions with highest values are bars and restaurants (I 56), some divisions of section S (repair of computers – S 95, personal service activities – S 96) and others related to entertainment (e.g. **R 92 – Gambling and gaming and R 93 – Sport and leisure associations**) (see the table below and the Annex for full results).

Principal component 2 (PC2) – Cash-intensiveness

The second component groups together the **two measures of cash-intensive businesses**: current assets and cash on total assets. It contributes to 23% of overall variability in the model. The top ranked sectors according to the PCA scores are motion picture, video and TV production (J 59), travel agencies (N 78). Some divisions pertaining to professional, scientific and technical activities can be identified (section M).

Principal component 3 (PC3) – Business profitability and cash

The third component explains 16% of the overall variability in the model, and it is associated with proxies for **gross profitability** and **cash-intensiveness**. The top NACE divisions with respect to this component score are still in the ICT sector, especially J 59 (Motion picture, video and television programmes) and J 61 (Telecommunications). Divisions N 77 (Rental and leasing activities), E 36 (Water collection treatment and supply), H 52 (warehousing and support activities for transportation) and R 92 (Gambling and betting activities).

Principal component 4 (PC4) – OC infiltration

The fourth and last component is related to **mafia-OC infiltration**. It accounts for 14% of the variability of the model. The business sectors ranking highest are those which also frequently appear in mafia investigations and asset recovery operations: e.g. divisions C 19 (Manufacture of coke and refined petroleum products) and C 23 (Manufacture of other non-metallic mineral products) – both related to the **production of cement** – B 08 (other mining and quarrying) and R 92 (Gambling and betting activities).

The table below presents, for each PC, the 10 NACE divisions with highest extracted values.

Table 23 – PC scores by business sector
Top 10 NACE divisions per each PC

RANK	PC1 Opacity and irregular labour	PC2 Cash- intensiveness	PC3 Business profitability and cash	PC4 OC infiltration
1	I 56	J 59	J 59	C 19
2	S 95	N 79	J 61	B 08
3	S 96	P 85	N 77	C 23
4	A 03	E 39	E 36	R 92
5	R 90	M 73	H 52	J 60
6	R 93	M 74	R 92	E 38
7	R 92	C 28	J 60	F 41
8	A 01	Q 88	H 50	R 93
9	A 02	S 94	I 55	I 56
10	M 74	N 81	K 64	H 52

Source: Transcrime – UCSC elaboration

STEP 6 – AGGREGATION AND COMPOSITE INDICATOR CONSTRUCTION

The principal components, identified through the PCA, are then combined into a synthetic composite indicator of ML risk at business sector level. As in the analysis at provincial level (see 2.2), they are **aggregated using as weights the proportion of variance** (of the model) explained by each PC, and then normalised to the scale 0-100 according to a min-max criterion, where 100 = highest ML risk. In other words (see Annex for details):

$$ML\ RISK\ INDICATOR\_SCORE_i = \sum_{j=1}^{J}(S_{ij} \times w_j) =$$

$$=(S_{1i} \times w_1)+(S_{2i} \times w_2)+(S_{3i} \times w_3)+(S_{4i} \times w_4)$$

where i = 1, .., I business sectors at NACE division level (in our case I = 77), j = 1, … , J component (J = 4) and w_j = proportion of variance (out of the total variance explained by the model) explained by each of the four components. Sij is the relevant value extracted by the PCA for each sector and for each component.

Table 24 below presents the top 10 and lowest 10 NACE divisions of the Italian economy ranked according to the overall ML risk. The **top four belong to sections I (Accommodation), S (Other service activities), R (Entertainment) and J (ICT)**. In particular, the hypothesis that bars and restaurants (I 56) could be exposed to the risk of money laundering is confirmed. Sector S is characterised by high levels of irregular labour, cash-intensiveness and opacity of the ownership structure: it includes both repair services (S 95) and activities related to **associations and organisations** (S 94) which have attracted attention for possible ML and TF uses (FATF, 2013a). But it also includes personal services businesses (S 96) which is a very broad category including **massage parlours, hair-dressers, laundromats, funeral parlours** – but also security companies and fiduciary services.[44]

Gambling and betting agencies (R 92) also rank high, as well as R 93, which includes a variety of vulnerable activities (with past OC infiltration evidence) such as **VLT (video-lottery)** or **beach facilities (*stabilimenti balneari*)**. Among other business divisions to be highlighted is N 79: the risk of **travel agencies** may be related to their close relationship with touristic industry and also to the possibility that they can provide **money transfer** services and therefore be vulnerable to ML purposes. Finally, divisions F 43, C 19, N 81, M 74 are all related to the **construction supply chain**, from the extraction of sand to the establishment and management of building sites (professional activities such as landscaping, architecture and civil engineering professionals and intermediaries).

Sector J ranks high only when a measure of business profitability is included in the model (Model 1). If this proxy is dropped (Model 2), it ranks much lower (see Table 25). Under Model 2 the PCA identifies three components (instead of 4), and as expected the variability explained by the PC related to mafia infiltration increases. Some divisions, like **Manufacturing of coke (C 19) and Gambling (R 92), score higher** than in the previous table. Apart from this, the results seem quite consistent because divisions belonging to **sections I (Accommodation) and section S (Other service activities) still rank highest**.

Among the sectors ranking lowest in both the models are **K (Financial sector) and C (Manufacturing)**. It is interesting to note that Section K includes AML obliged entities such as banks, financial institutions or insurance companies. On the other hand, the manufacturing sector is usually a capital-intensive industry characterized by high barriers to entry which make organised crime infiltration and money laundering through cash injection both unlikely (except for some divisions).

44. There are specific NACE divisions for these business sectors, respectively N 80 and K 66 / K65. However, the review of all Italian companies registered in S 96 revealed a very high number of security companies and of fiduciary services. It is difficult to understand why these businesses preferred registering in such class of economic activity than in their 'proper' ones. But this represents a weakness of the current economic activity nomenclature – which also reflects on IARM methodology.

Table 24 – ML risk composite indicator across NACE divisions in Italy

Top 10 and least 10 risky divisions. Model 1 including business profitability

Business Sector (NACE division)	PC1 Opacity and irregular labour	PC2 Cash-intensive-ness	PC3 Business profitability and cash	PC4 OC infiltration	ML RISK COMPOSITE INDICATOR
I 56. Food and beverage service activities	100.0	48.2	17.3	20.4	**100.0**
J 59. Motion picture, video and television programme production	15.3	100.0	100.0	8.3	**79.0**
S 95. Repair of computers and personal and household goods	75.2	62.1	6.0	4.8	**77.6**
R 92. Gambling and betting activities	50.2	44.2	37.2	37.3	**73.2**
R 90. Creative arts and entertainment activities	53.9	60.2	27.7	10.3	**69.9**
S 96. Other personal service activities	71.7	34.2	13.1	6.6	**67.5**
N 79. Travel agency tour operator reservation service	44.3	82.1	14.4	11.9	**66.9**
M 74. Other professional scientific and technical activities	44.4	75.1	22.9	7.8	**65.9**
P 85. Education	41.8	81.2	16.1	10.0	**64.7**
R 93. Sports activities and amusement and recreation activities	50.7	27.2	25.1	23.1	**58.5**
D 35. Electricity gas steam and air conditioning supply	4.6	38.9	27.1	6.4	**23.3**
C 30. Manufacture of other transport equipment	0.8	50.0	9.4	18.9	**22.9**
E 36. Water collection treatment and supply	3.5	31.4	38.9	0.0	**21.5**
C 20. Manufacture of chemicals and chemical products	1.3	56.1	9.0	5.0	**20.8**
C 16. Manufacture of wood and of products of wood and cork	7.4	44.8	6.1	3.3	**19.7**
C 24. Manufacture of basic metals	0.0	47.9	4.9	2.4	**14.6**
C 29. Manufacture of motor vehicles trailers and semi-trailers	1.7	41.6	1.2	6.3	**13.5**
H 53. Postal and courier activities	15.5	6.8	6.8	3.2	**11.7**
K 66. Activities auxiliary to financial services and insurance activities	7.1	5.1	9.8	3.8	**5.9**
K 65. Insurance, reinsurance and pension funding	5.3	0.0	2.9	2.8	**0.0**

Source: Transcrime – UCSC elaboration

Table 25 – ML risk composite indicator across NACE divisions in Italy
10 most and 10 least risky divisions. Model 2 excluding business profitability

Business Sector (NACE division)	PC1 Opacity and Irregular labour	PC1 Cash intensiveness	PC3 OC infiltration	ML RISK COMPOSITE INDICATOR (no profitability)
I 56. Food and beverage service activities	100.0	47.0	21.0	**100.0**
S 95. Repair of computers and personal and household goods	77.4	57.0	3.2	**80.4**
S 96. Other personal service activities	72.6	32.8	6.5	**67.3**
N 79. Travel agency tour operator reservation service and related activities	42.3	76.6	11.2	**64.4**
R 92. Gambling and betting activities	44.8	45.8	40.5	**63.5**
R 90. Creative arts and entertainment activities	48.2	59.7	12.2	**62.1**
P 85. Education	40.2	75.5	9.2	**61.6**
A 03. Fishing and aquaculture	58.5	42.9	6.9	**61.0**
M 74. Other professional scientific and technical activities	42.1	70.5	7.7	**60.4**
C 19. Manufacture of coke and refined petroleum products	3.4	61.2	100.0	**59.1**
H 50. Water transport	15.3	18.0	5.3	**16.0**
K 64. Financial service activities except insurance and pension funding	3.8	25.1	19.7	**15.3**
J 61. Telecommunications	8.3	24.3	9.8	**14.9**
C 29. Manufacture of motor vehicles trailers and semi-trailers	3.6	36.8	4.1	**14.6**
D 35. Electricity gas steam and air conditioning supply	2.1	37.1	7.0	**14.6**
C 24. Manufacture of basic metals	0.9	42.9	0.5	**13.9**
H 53. Postal and courier activities	15.3	7.2	3.1	**10.6**
E 36. Water collection treatment and supply	1.4	30.2	1.1	**9.0**
K 66. Activities auxiliary to financial services and insurance activities	7.2	5.1	3.6	**3.6**
K 65. Insurance, reinsurance and pension funding except compulsory social security	6.2	0.0	2.0	**0.0**

Source: Transcrime – UCSC elaboration

STEP 7 – SENSITIVITY ANALYSIS AND VALIDATION

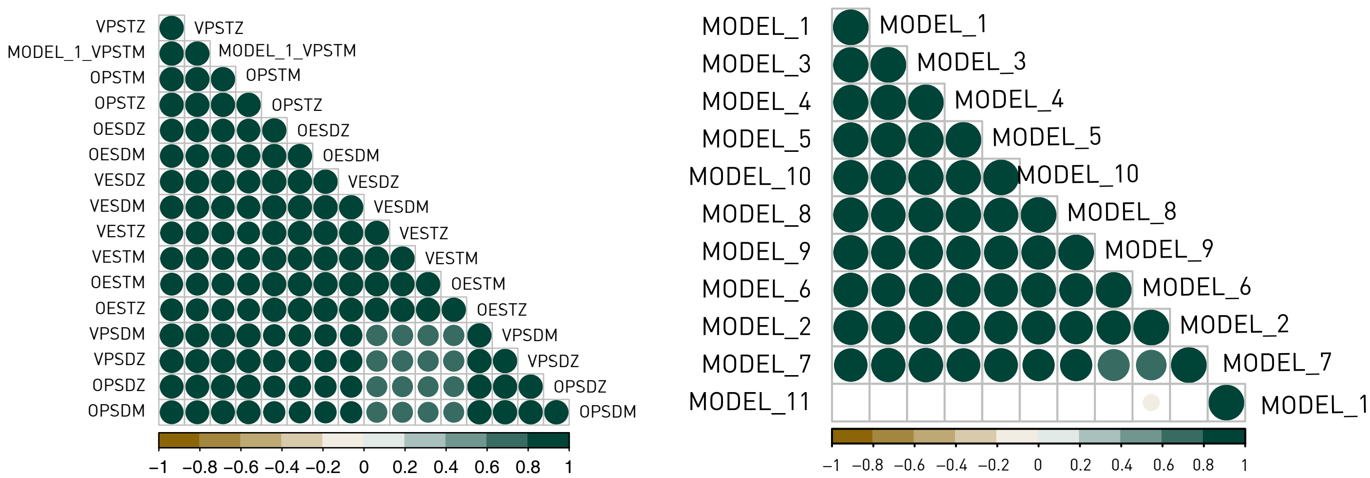
The composite score developed at business sector level cannot be validated, like the provincial one, against alternative measures of money laundering such as **suspicious transaction reports** or **ML offences** because data on STRs are not available by industry (it is not mandatory information to be given in the STR form).

For this reason, the validation process is limited to only the **sensitivity analysis**. As in the PCA at provincial level, two types of changes are taken into account:

- variations in the parameters used to compute the final composite indicator[45]
- modifications in the variables selected for the PCA, dropping one variable at a time from the final model (Model 1).

All the indicators' scores resulting from changes to PCA parameters or variables are **highly correlated**, with an average **r = 0.94** excluding Model 11. Model 11 (which includes business opacity proxies not weighted by average company size) has instead a weak positive correlation with the other models. The correlation matrix suggests that changes in the methodology do not significantly affect the overall result, and that the **IARM ML composite indicator remains solid and robust** even after the sensitivity analysis.

Figure 29 – Correlation among ML risk composite indicators after applying different methodological options (left) or using different proxy variables (right)



Source: Transcrime – UCSC elaboration

45. See 2.2 (and in particular Table 18) and the Annex for details. Each of the parameters corresponds to a letter: V (Varimax), O (Oblimin), P (Weights based on the proportion of variance explained), E (Equal weights), S (Weighted arithmetic mean), T (Components standardised Z-scores), D (Components normalised Min – Max), M (Risk indicator normalised Min – Max), Z (Risk indicator standardised Z-scores).

2.4 Research and policy implications

This chapter carried out an exploratory analysis of ML threats and vulnerabilities in Italy. It developed two composite indicators of ML risk:

- at **sub-national area level**, across the 110 Italian provinces
- at **business sector level**, across 77 NACE divisions.

What is the added value of this analysis?

IARM **complements existing ML/TF risk assessments** conducted in Italy in recent years such as the NRA 2014 (CSF, 2014b). It stresses the quantitative approach and incorporates some innovative elements:

- A **higher disaggregation detail**: IARM carries out a sub-national analysis, while the NRA adopts a national perspective.
- **Coverage of all business sectors**, while the NRA does not adopt a sectorial perspective.
- **A synthetic measure**: the composite indicators developed by IARM condense into one value a complex and multifaceted phenomenon such as ML risk, while it is difficult to summarise the results of existing NRA in a 'snapshot'.
- **An innovative analysis of Italian businesses' ownership**: IARM has carried out the first large-scale investigation of where the shareholders and BOs of Italian companies come from and of how complex their ownership structure is across regions and business sectors.

Despite the innovative contribution, the approach adopted by IARM has various weaknesses:

- It does not take into account ML threats important for the Italian context such as **corruption, extortion and usury** – for which reliable measures at regional and business sector level do not exist.
- It does not fully take into account **emerging threats and vulnerabilities**, which, by definition, are characterised by lack of data and estimates: for example, the use of virtual currencies and new payment methods (e.g. prepaid cards, mobile or internet based payments).
- It does not consider the vulnerabilities in the Italian AML regulation, because it is assumed that they are the same across regions and sectors, on which the analysis is focused.
- It does not analyse the **consequences** of ML in Italy, despite the large body of evidence of the negative impact of money laundering (especially of mafia groups) on market competition and economic growth.

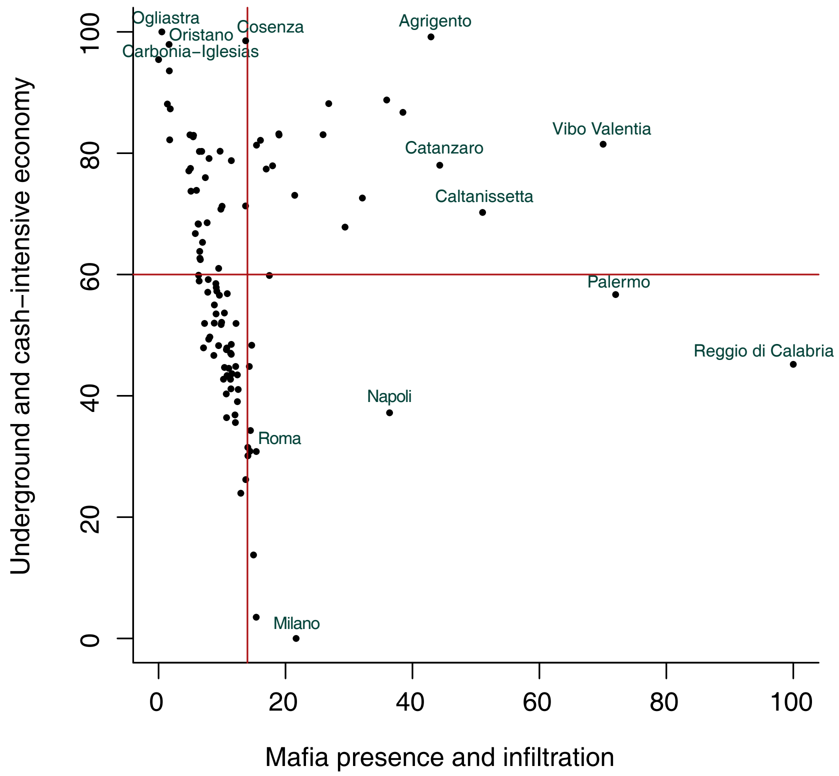
Who can benefit from this analysis?

Supervisory authorities

The first to benefit from IARM results are supervisory bodies at the national level (e.g. MEF, Banca d'Italia), at industry level (e.g. national banking association, Ordine dei Dottori Commercialisti e degli Esperti Contabili, etc) and other public authorities (e.g. Agenzia delle Entrate, CONSOB, Camere di Commercio, etc.). IARM supports the design of more **evidence-based policies** because it makes it possible to disentangle, for each province and business sector, the factors that contribute most to the overall ML risk. This can lead to better area- or sector-specific interventions.

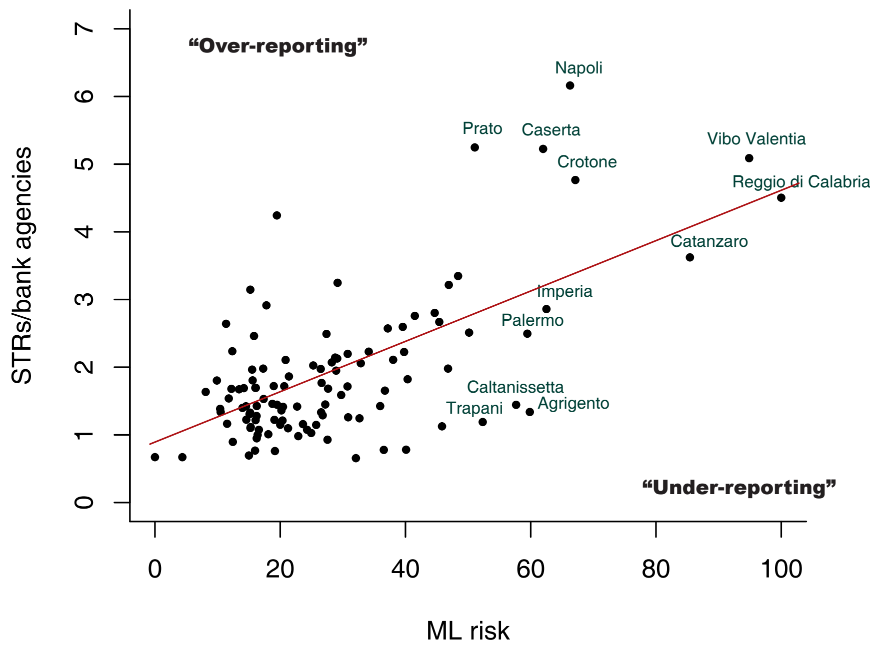
For example, the scatterplot below **compares two risk components** stemming from the analysis at province level: PC1 (OC infiltration) and PC2 (underground and cash-intensive economy). It shows how the 110 Italian provinces distribute along the two axes. Provinces like Vibo Valentia or Catanzaro have high ML risk because of high values of both PC1 and PC2. Provinces like Ogliastra or Benevento, instead, have high ML risk determined by high levels of cash-use and of underground economy, but they have low ML risks related to OC and mafia. Provinces like Naples are characterised by high PC1 values (mafia component) but relatively lower values of cash use. This would **help policy-makers to understand better where to intervene** and what threats and vulnerabilities should be targeted specifically in order to reduce the overall ML risk.

Figure 30 – Scatterplot - OC infiltration vs. Underground and cash-based economy



Source: Transcrime – UCSC elaboration

Figure 31 – STRs and ML risk



Source: Transcrime – UCSC elaboration

From a policy-maker's perspective, this approach would also help in identifying the **under-** or **over-reporting** provinces according to their estimated level of ML risk. The figure below plots on the horizontal axis the ML risk composite indicator values, and on the vertical one, the STRs/banks ratio. Those provinces lying below the diagonal report fewer STRs than expected on the basis of their estimated level of ML risk, while those above the diagonal report more STRs than expected. Such a chart would help policy-makers and competent authorities to **understand the reasons for the different behaviour of different areas in terms of reporting to FIUs**, and facilitate the monitoring of obliged entities' activities.[46]

Investigative authorities

On the basis of the IARM analysis, investigators in the AML field (e.g. UIF, DIA, Guardia di Finanza, etc.) could improve the detection of the risky areas and sectors on which to f**ocus investigative efforts**. Moreover, the analysis of the **ownership structure of Italian firms** makes it possible to detect links with risky jurisdictions and anomalies which would warrant further investigation – above all, the high number of foreign beneficial owners (in particular from Spain) in sectors like R 92 (gambling and betting) characterised by growing criminal infiltration by organisations such as the Camorra and the 'Ndrangheta.

Obliged entities

Obliged entities subject to L. 231/2007 – like banks, professionals, real estate agencies and gaming/gambling companies – could use the IARM analysis to **enrich the set of anomaly indicators** for CDD purposes: for example, they may be useful to determine the risk related to the client's geographic area ("*area geografica di residenza o sede del cliente e della controparte*") and to its business activity ("*prevalente attività svolta*") (L. 231/2007, Art. 20, 1). IARM ML risk composite indicators could be easily adopted in the everyday work of AML practitioners and incorporated into proprietary AML risk models and software.

What future research directions?

Future research on Italian ML risk assessment would benefit greatly from the following measures:

- Improving the **availability and quality of data**:
  - related to those ML predicate offences which are particularly relevant to the Italian context, like corruption, extortion and usury, for which reliable sub-national measures are lacking;
  - related to tax evasion, especially at the business sector level;
  - on cash, in terms of use by both individuals and by businesses: surveys on this topic would be very helpful;
  - on STRs, especially improving the amount of information on business sectors involved in suspicious transactions;
  - related to business ownership, by integrating BvD data with information from the national Italian business register.
- **Integrating public statistics with private sector data**, e.g. with proprietary information of the banking industry or information held by sectorial supervisory authorities;
- **Integrating qualitative and quantitative approach**: the methodological approach experimented by IARM could be combined with the approach of the Italian NRA, and it could be enriched with a higher number of interviews and questionnaires in order to assist the selection of risk factors and to validate the results of the statistical analysis.
- Extending the analysis to further risk factors, such as vulnerabilities in the AML regulation, which become crucial when conducting cross-national comparative analysis.
- Exploring the possibility to **analyse and assess also impact/consequences of ML activities**, at least in selected areas of the country or business sectors.

If repeated over time, the IARM exercise could help to identify emerging ML trends and to monitor how ML risks vary, over time, across areas and sectors. For this reason, it is recommended to take account of the IARM methodology in the future update of the Italian NRA to be carried out in 2017.

46. Figure 31 assumes a linear relationship between ML risk score and STRs which in fact is not proven. Moreover, it does not consider important variables which could explain the different attitudes in reporting ML suspicious operations, such as the different nature and concentration of banks and professionals, the different reporting culture, the different guidelines issued by regional bodies. However, it serves only to provide policy-makers with a clearer idea of how this analysis could be used for AML monitoring purposes.

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3. The Netherlands

The Netherlands has been a pioneer in money laundering research (FATF, 2013a, pp. 54-55). The official National Risk Assessment has not yet been finished (it is expected in 2017), but a pilot study for the National Risk Assessment (NRA) was recently published (van der Veen and Ferwerda, 2016).

This chapter presents an analysis of the main ML risk factors in the country, providing details of how threats and vulnerabilities vary across business sectors (83 divisions).

The chapter is structured as follows: Section 3.1 provides an introduction on ML risk assessment in the country; Section 3.2 illustrates the analysis at business sector level and the development of a ML risk composite indicator; Section 3.3 discusses briefly research and policy implications.

Main findings - The Netherlands

- IARM has carried out an exploratory assessment of ML risk in the Netherlands, developing a composite indicator at business sector level, across **83 NACE divisions**
- The analysis provides possible inputs for the NRA that is developed in 2017

Money laundering risk assessment across 83 NACE divisions

- IARM has identified and collected data for **two threat factors** of money laundering risk with **four proxy threat variables**:

  1. Organised crime infiltration
     a. Organised Crime Monitor cases
     b. Evidence reported in the EU-project Organised Crime Portfolio
     c. Administrative measures to prevent organised crime infiltration
  2. Corporate fraud
     a. Corporate tax anomalies

- IARM has identified and collected data for **three vulnerability factors** of money laundering risk with **five proxy threat variables**:

  1. Cash intensiveness
     a. Cash / total assets
  2. Opacity of business ownership
     a. Distance between company and beneficial owners
     b. Risk score for shareholders
     c. Risk score for beneficial owners
  4. Business profitability (the more profitable, the more vulnerable to ML)
     a. EBITDA margin

- These nine risk factors are combined in a **composite indicator of ML risk** using a principle component analysis

- According to the model, the economic sector in the Netherlands with the highest ML risk are **casinos and other gambling and gaming businesses** (NACE division R 92). They can be an interesting target for organised crime investments but can also be used to launder money itself. While casinos were already part of EU AML regulations in the Third EU directive, the Fourth EU directive extended obligations also to other gaming and gambling activities. The FATF published a report in 2009 about the vulnerabilities of casinos and the gaming sector. The related sector R 93 – Sport, amusement and recreation activities, which includes also prostitution services – is slightly lower in the list, but still in the top 10.

- **Hotels** (accommodation, I 55) come second. They score particularly high on the principal component of OC infiltration, indicating that criminals see them as interesting investments. **Bars and restaurants** (I 56) are slightly lower on the list, but still in the top 10 for the same reason.

- Third is the **art and entertainment sector** (R 90), for which the confidentiality (of the customers) is especially mentioned in the literature as a ML risk factor. Here, this sector is also associated with a high level of opacity of the businesses' ownership structure.

- **Security and investigation agencies** (N 80) are fourth in terms of ML risk index for the Netherlands. The Dutch police published a report in 2014 with several indications that organised crime groups (among them, outlaw motorcycle gangs) are active in this sector.

- Sectors which are usually under the lens of AML investigators – like **financial institutions, real estate agencies and trust and company service providers** – do not rank very high according to the IARM estimate: but their exposure to ML is usually related to their role as *gatekeepers* (i.e. in the *placement* phase of the ML process), while IARM is somehow focusing on the *integration* phase of the ML cycle.

Table 2 – ML risk across business sectors in the Netherlands
Top 10 NACE divisions according to ML risk composite indicator

Business sector (NACE division)	ML RISK COMPOSITE INDICATOR SCORE
R 92. Gambling and betting activities	100.0
I 55. Accommodation	97.9
R 90. Creative, arts and entertainment activities	72.9
N 80. Security and investigation activities	69.8
S 95. Repair of computers and personal and household goods	54,4
N 79. Travel agency, tour operator reservation service and related activities	54.1
Others S 96. Other personal service activities	48.7
O 84. Public administration and defence; compulsory social security	46.6
R 93. Sports activities and amusement and recreation activities	44.0
I 56. Food and beverage service activities	43.8

Source: VU Amsterdam elaboration

Research and policy implications

- The indicators and results produced by IARM respond to the need, stressed by regulatory developments at the EU level and the pilot study for the Dutch NRA ML, to develop **more objective and solid methodologies** for ML risk assessment

- In particular they can be used by, for example:

  - **Policy-makers**, to design more evidence-based and specific interventions
  - **Investigators**, to identify anomalies and emerging ML trends more easily (if the exercise is repeated over time)
  - **Obliged entities** (e.g. banks or professionals), to facilitate customer due diligence (CDD) and assessment of clients' risks

- However, the IARM quantitative assessment cannot completely replace the qualitative approach proposed in the pilot study for the Dutch NRA ML; rather it should be seen as supplementary. A **combination of the two approaches** is suggested to fully appreciate overall ML risks in the country.

- Future developments should improve **data availability and quality**, refine proxies for risk factors and explore alternative variables and measurement approaches.

3.1 Introduction and background

Although an official NRA is still to be published in 2017, references can be made to four relevant studies on money laundering risk in the Netherlands:

1) The **National Threat Overview** by the National Police Services Agency (Soudijn & Akse, 2012)
2) A **Policy Effectiveness Evaluation** by the Court of Audit (Algemene Rekenkamer, 2014)
3) The **FATF Mutual Evaluation of the Netherlands** (FATF, 2014b)
4) The first **National AML Policy Monitor** published in October 2015 (Decide, 2015)

National Threat Overview

The National Police Services Agency provides an overview of organised crime threats in the Netherlands, including a specific report on money laundering (Soudijn & Akse, 2012). The report describes **money laundering methods** (primarily in qualitative terms but including - as far as possible - some figures and indicators), characteristics of **persons involved in ML cases, consequences for Dutch society, relevant factors** (the abuse of the 500 Euro notes), and some **specific conclusions** about the near future, including the prediction that the basic ML methods will remain the same and that only the specific ways in which these methods are used will change, due to changes in society and regulation. The report concludes that traditional methods such as loan back and feigning a higher turnover are still frequently used, and that methods such as ABC-transactions are particularly suited to laundering larger sums of money. Potential new trends may include trade based money laundering (TBML), the use of specific Dutch legal entities (e.g. *'Stichtingen'*), new payment methods (such as prepaid debit cards), and leasing cars (whereas leasing companies are not part of the obliged entities in Dutch AML legislation).

According to the report, the consequences for Dutch society as a whole are hard to estimate, but on a local level clear examples of risky situations exist, such as monopoly positions (shops), important local positions through investments in real estate, and criminals as negative role models for adolescents in local neighbourhoods. Transfer of illegal proceeds to other countries is mentioned as well, but it was not part of the Dutch National Threat Overview.

Policy Effectiveness Evaluation

The Court of Audit (Algemene Rekenkamer, 2014) conducted a **policy evaluation on the anti-money laundering policies in the Netherlands**, following up on an earlier, very critical, report (2008) concluding that the prevention of money laundering was insufficient, that the chance that money laundering was detected and punished was low, and that investigating agencies and authorities made too little use of the opportunities to seize illegal assets. The report concludes that investments have been made into capacity, expertise, and exchange of information, but that the responsible Ministers are unable to provide insight into the predominant money laundering risks and the results of anti-money laundering policies. Furthermore, feedback to obliged entities about what investigating agencies do with reported suspicious transactions has not improved. Finally, the insight of the Dutch FIU into this matter has even decreased, according to the Court of Audit. The advice of the report is to gain insight into the predominant money laundering risks in the Netherlands and to start collecting and analysing quantitative and qualitative data on the activities of agencies involved in anti-money laundering. The Ministers agreed to follow up on this advice, but stated that the report gives a too limited view of all the activities that are carried out in the fight against money laundering in the Netherlands (Algemene Rekenkamer, 2014).

FATF Mutual Evaluation of the Netherlands

The FATF 2nd Follow-up report (FATF, 2014b) of the 2011 Mutual Evaluation of the Netherlands provides an evaluation of the policies and activities implemented in the Netherlands in response to the recommendations of this Mutual Evaluation. The **amendments of preventive AML/CFT legislation have (largely) addressed the majority of the shortcomings**, including those on beneficial ownership requirements. Furthermore, the report concludes that the Netherlands has made important progress by criminalising terrorist financing as an autonomous offence. The key recommendation of the report is that the Netherlands has made sufficient progress in addressing the deficiencies identified in the earlier Mutual Evaluation Report, so that its overall level of compliance can be assessed at a level essentially equivalent to 'Largely Compliant'.

National AML Policy Monitor

The National AML Policy Monitor (Decide, 2015) was partly developed as a response to the critical reports of the Court of Audit. This AML Policy Monitor will contribute to the establishment of **(performance) indicators of AML activities that are achievable, measurable, and adequate**. The first step includes an inventory and interpretation of the AML activities and exchange of information between the actors involved. Seven processes are distinguished: (collection) of evidence on money laundering; investigation and tracing; prosecution and trial; Dutch FIU: detection of suspicious financial transactions; reporting unusual transactions and identifying clients by institutions (in compliance with the WWFT, the law on money laundering and terrorist financing); supervision of institutions for compliance with AML requirements; and directing and coordinating of the AML activities. The second step involves measuring these activities against the FATF criteria for an effective AML policy. After this first report (Decide, 2015), the next version of the monitor intends to specify the performance indicators further, which will improve the functionality of this National AML Policy Monitor.

IARM builds on these four studies (and further ones). But it provides an added value by incorporating some innovative elements:

- IARM focuses on the **relative ML risk** in different business sectors in the Netherlands, while these studies focus on the overall policies and threats
- IARM covers the ML risk of **all the economic sectors**, while the four former studies focus mainly on regulated sectors (i.e. financial intermediaries, DNFBPs and other entities);
- IARM adopts a **quantitative approach** which ultimately produces a composite indicator of ML risk. This could become an operational instrument not only for policy-makers, but also for LEAs in AML investigations, supervisors and obliged entities during CDD activities. Eventually it could also be used to increase the effectiveness of money laundering detection by various institutions, such as the police, the financial police (FIOD) and the Tax Office.

As a result, IARM is **fully complementary** to the previous exercises and their future updates. The combination of the findings of IARM and the previous studies should contribute to a more in-depth understanding of the ML risks in the different business sectors.

3.2 Analysis at business sector level

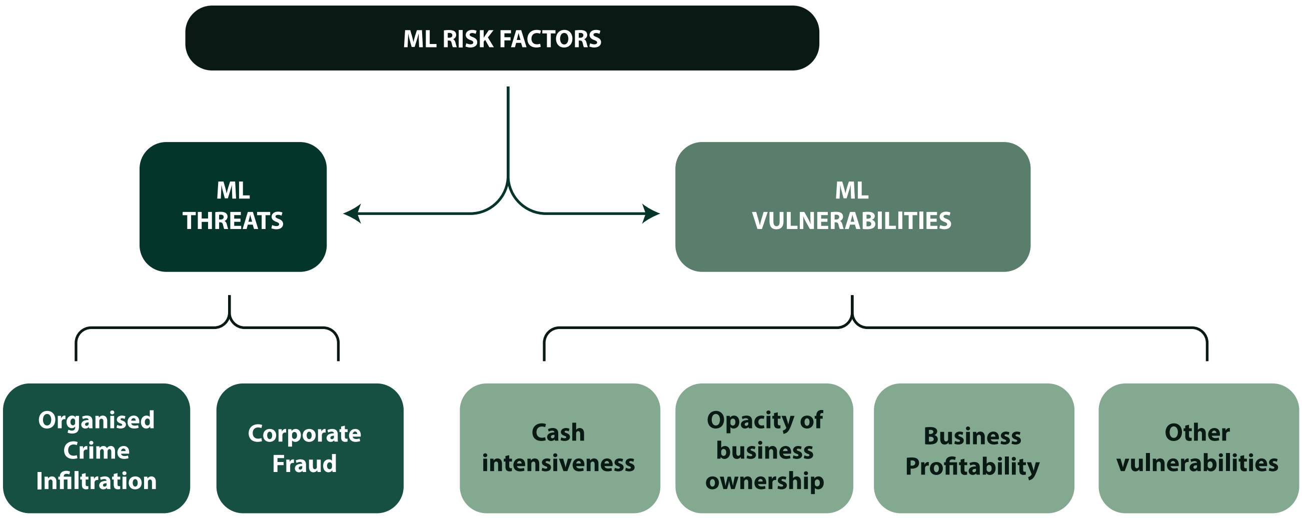
The composite risk indicator is calculated for **83 business sectors**[47] **(level 2 NACE-classification, i.e. NACE divisions)**. This disaggregation level is the best compromise in terms of guaranteeing statistical significance and data availability (e.g. each sector should have sufficient companies for which data is available).

STEP 1 – ML RISK FACTORS IDENTIFICATION

After a review of academic literature, institutional reports, investigative and judicial evidence, and validation by experts, IARM has identified a number of ML risk factors for business sectors in the Netherlands that can be operationalised. They are grouped into **threats, vulnerabilities and consequences** in line with the FATF taxonomy (CSF, 2014a; FATF, 2013a; Dawe, 2013).[48]

For each risk dimension, a variety of risk factors is identified. They are presented in the following chart and discussed in detail below. For the purpose of measurement, each risk factor is operationalised into one or more **proxy variables**. These variables are then used to produce the ML risk composite indicator.

Figure 32 – Money laundering risk factors at business sector level in the Netherlands



Source: VU Amsterdam elaboration

47. Those business sectors that include on average fewer than 10 registered companies according to the company data from the Statistics Bureau Netherlands (CBS) in the quartiles of 2014 and 2015 have been removed. In particular, four sectors have been removed (NACE Rev. 2 Divisions): B 05. Mining of coal and lignite, T 97. Activities of households as employers of domestic personnel, T 98. Undifferentiated goods- and services-producing activities of private households for own use and U 99. Activities of extraterritorial organisations and bodies.

48. In line with the 2014 NRA and on the on-going EU SNRA, the main focus is on threats and vulnerabilities, while consequences are only briefly discussed (see Section 1.4).

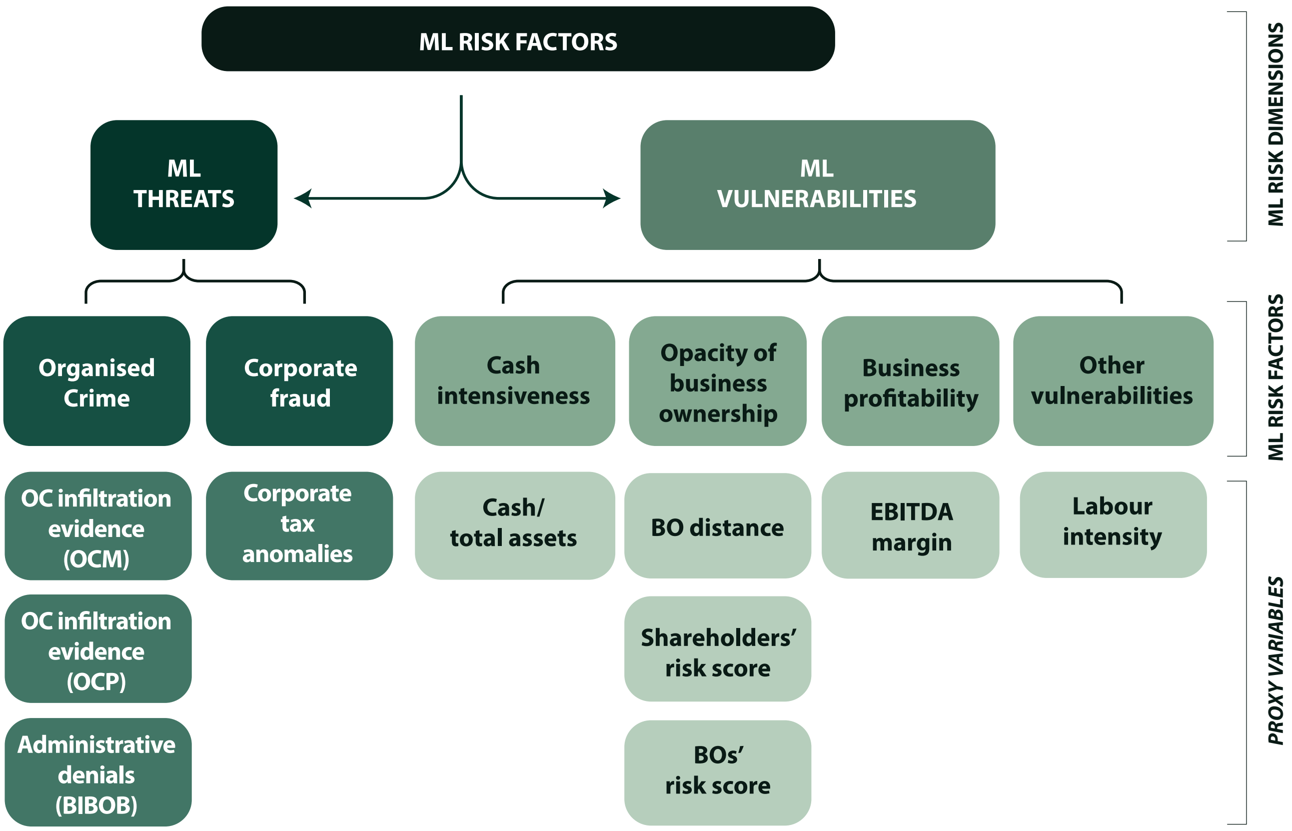
STEP 2 – ML RISK FACTORS OPERATIONALISATION

Each dimension, and in particular each risk factor, is operationalised into multiple **proxy variables** in order to allow for their measurement and analysis. Proxies are identified according to previous literature and data availability and applicability (see Chapter 1 and Annex). The chart below illustrates the selected proxies.

For the purpose of the PCA presented in this section, only those risk factors that could be operationalised with available and applicable data and proxies at business sector level are considered. For this reason, the statistical analysis **does not cover some risk factors that are deemed important in the literature** (such as irregular labour), because in the Netherlands there are no good measures available at the business sector level.[49]

Annex A3 lists for each variable, the relevant source, the time coverage and any other relevant comments. The rationale behind the selection of each proxy variable was already briefly mentioned above and will be detailed in the Annex, and is therefore not discussed here. Mainly due to data availability, the selected proxies differ slightly between the analysis for Italy, the UK and the Netherlands.

Figure 33 – Money laundering risk factors and their proxy variables at business sector level in the Netherlands



Source: VU Amsterdam elaboration

49. We focus on the level 2 NACE classification.

Money laundering threats

Focus is posed on the ML threats for business sectors in the Netherlands that can be measured with available data. For an analysis on business sectors, **the threat variables are particularly hard to find**, since crime data cannot be used as in a geographical analysis. Crimes happen in a certain region, but not always in a specific sector.[50] Eventually 4 proxies were found for ML threats. Data are available from research reports on organised crime investments in the legitimate economy (Kruisbergen, van de Bunt, & Kleemans, 2012; Savona & Riccardi, 2015) and investigations for administrative laws specifically designed to limit the threat of crime money being invested in the regular economy. With respect to indications for corporate tax anomalies we have unique and confidential data from the tax office on anomalies in the financial/tax administrations of companies detected by tax officers during a tax inspection.

Organised crime infiltration

Cases of OC investments/infiltration

One of the most important sources for insights into organised crime infiltration in the Netherlands is the so-called 'organised crime monitor' (Kruisbergen et al., 2012). See the box below for a description and the main results of this study.

Organised Crime Monitor in the Netherlands

Kruisbergen, Kleemans and Kouwenberg (2015) discuss national and international studies on investments of organised crime offenders and use empirical data from the Dutch Organised Crime Monitor to give empirical insight into the choices that organised crime offenders make when they invest their money in the legal economy.

The data consist of a dataset of **1,196 individual assets of (suspected) participants in organised crime**. This dataset covers various crimes, such as different sorts of drug trafficking/production, human smuggling, human trafficking and illegal arms trade, but also (large scale) fraud and money laundering. Furthermore, the dataset includes information on foreign assets. To build this dataset, use was made of all 150 cases that were analysed by the research team of the Dutch Organised Crime Monitor (Kruisbergen et al., 2012), a long-running research project on organised crime in the Netherlands. The main sources of information are closed Dutch criminal investigations into criminal groups (period: 1996-2011), containing information on many hundreds of suspects.

Using this dataset of 1,196 individual assets, the study sheds light on the kind of assets that offenders purchase and where these assets are located. The results are used to assess the tenability of different theoretical approaches and assumptions that are present in the literature: the standard economic approach ('profit'), the criminal infiltration approach ('power') and social opportunity structure ('proximity'). The results of this study show that **offenders primarily invest in their country of origin or in their country of residence**. Furthermore, their investments consist of **tangible, familiar assets such as residences and other real estate and (small) companies** in well-known sectors: wholesale and retail (e.g. import/export companies, car companies, clothing firms, and 'coffee shops' – i.e. condoned Dutch cannabis outlets), hotels, bars and restaurants, transportation companies, brothels, and 'financial intermediation' (management or investment companies which main purpose is to hold other assets, such as real estate).

Investments such as bonds, options, and stocks in companies in which offenders are not personally (or indirectly) involved, such as stocks listed on the stock exchange, were only found in a small number of cases. In other words: offenders usually stay close to home with their investments. Hence, instead of profitability and power, proximity seems to be a better description of their investment choices.

50. Obviously, some crimes do happen in a specific sector, like stealing from the company assets or like specific types of fraud. But these crimes are not the money laundering threats for the business sectors investigated here; they are merely the sources of crime money that can later threaten other business sectors.

The IARM project gained access to the data of the Organised Crime Monitor.[51] It is known for all the 150 organised crime cases whether they invested in companies and to which business sectors these companies belong.[52] These data are used as one of the **proxy variables for organised crime infiltration**.

Another proxy variable for organised crime infiltration comes from data of an international EU co-funded research project called **Organised Crime Portfolio** (OCP) (see Savona & Riccardi, 2015). The OCP project based its conclusions on a database built by collecting information on organised crime investments from publicly available sources (research reports, newspapers, etc.). This means that there is some overlap of the data with the Organised Crime Monitor in the Netherlands, which are also covered by the OCP project.[53]

Given the concerns about overlap, the correlation between the OCP data and the Organised Crime Monitor data is calculated to indicate whether the data are too similar. The correlation of 0.26 makes us conclude that the data sources are sufficiently different and that therefore both can be included in the analysis.

Administrative law and background checks

Especially in Amsterdam in the 1990s, there were concerns in the Netherlands about criminals taking over (parts of) the city centre (Commission Van Traa, 1996). Consequently, to limit criminal investments in businesses such as bars and restaurants, the Netherlands implemented the so-called **BIBOB Act** that gives administrative institutions the opportunity to **revoke or reject licences when there is suspicion of criminal involvement.** Since the BIBOB Act came into effect, the Netherlands has become the second European country, after Italy, with administrative regulations against organsed crime (Ferwerda & Unger, 2016). An internal evaluation of the BIBOB Act showed that the possibility of being screened discouraged several applicants from continuing the application process for a licence and possible effects of displacement (Huisman & Nelen, 2007).

As a proxy for organised crime infiltration, use is made of data on the number of BIBOB investigations in different business sectors. Ideally, data on the results of these investigations (how often in each business sector licences are revoked or rejected) would be preferred but unfortunately they are not available because confidential. Therefore, data on how often a BIBOB advice is given in each business sector is used as a proxy for potential OC infiltration (see Landelijk Bureau Bibob, 2014).[54]

Corporate tax anomalies

Money launderers using a company for their money laundering operations have an objective different from that of normal business owners, who generally aim to maximize profits or the size of the company. This difference should somehow be reflected in their behaviour, which may trickle down into the administration of a company. A money launderer may use some dirty funds – to pay employees with *black* salaries, for example, or add cash to the register – and must find a way to account for them; some **accounting manipulations (**or **'cooking of books') might therefore be necessary.** In an attempt to capture this behaviour, we use data on financial inspections by the Tax Office.

It was possible to acquire[55] confidential data from the Dutch Tax Office on how many companies have been subject to a financial inspection[56] and **how often corrections to the financial statements were made in each business sector** (at division level) for the years 2011-2015. If a tax inspector finds a mistake in the financial administration of a company, a correction of the tax declaration is made.[57] These data are used as a proxy for potential corporate fraud. [58]

51. We thank Edwin Kruisbergen and the scientific research and documentation centre of the Dutch ministry of security and justice (WODC) for providing us with the detailed data and allowing us to use them for this research project.

52. To make the data comparable across sectors, we divide the count by the total number of registered companies in that business division. In some cases we did not have data specified at business division level, but only at the business section level. In those cases we divide the number of invested companies by the sum of all the registered companies in all the different divisions belonging to that section and applied that result to all the divisions belonging to that section.

53. However, these cases are reclassified by the authors of OCP based on the short descriptions of all cases included in the Organised Crime Monitor (in an appendix), since they did not have access to the (unpublished) original data classification that it is now used.

54. By definition, these data only apply to a limited number of business sectors: sectors that are eligible for a BIBOB investigation. Which sectors are eligible for a BIBOB investigation is not nationally prescribed, but differs from city to city.

55. We would like to thank the Dutch Tax Office for providing the data and Jan Glimmerveen for his help in acquiring the data.

56. The official term in Dutch for such an investigation is a "boekenonderzoek".

57. It was not possible to know which corrections were made and whether it was to the advantage or disadvantage of the checked company, but only the mere amount of corrections was available. To construct a comparable proxy variable across sectors, the numbers of corrections in each sector for the five years 2011-2015 were added up and then divided by the total number of inspections in that sector in the same period.

58. Obviously, it is not possible to know whether these corrections are (part of) corporate fraud: this is only the best indicator available for such a complex and multifaceted phenomenon as corporate tax fraud.

Money laundering vulnerabilities

Cash-intensiveness

As described in Chapter 1, cash-based economies are more vulnerable to money laundering. Cash is a facilitator for committing crimes (first of all tax evasion) and for laundering the proceeds of crime. It is **hard to trace** and therefore it **helps to disguise the criminal sources** of profits, making financial investigations and asset seizures harder (Riccardi & Levi, 2017; Europol, 2015; U.S. Department of the Treasury, 2015; Soudijn & Reuter, 2016).

The cash intensity in the Dutch economy as a whole is relatively low when compared to other European countries - according to a 2011 household survey conducted by the European Central Bank (ECB, 2011), as can be seen in the table below. After 2011, the amount of cash payments decreased even further, from 4.13 billion payments in 2011 to 3.19 billion payments in 2015 (DNB, 2015).

Table 26 - % purchases made in cash by price range

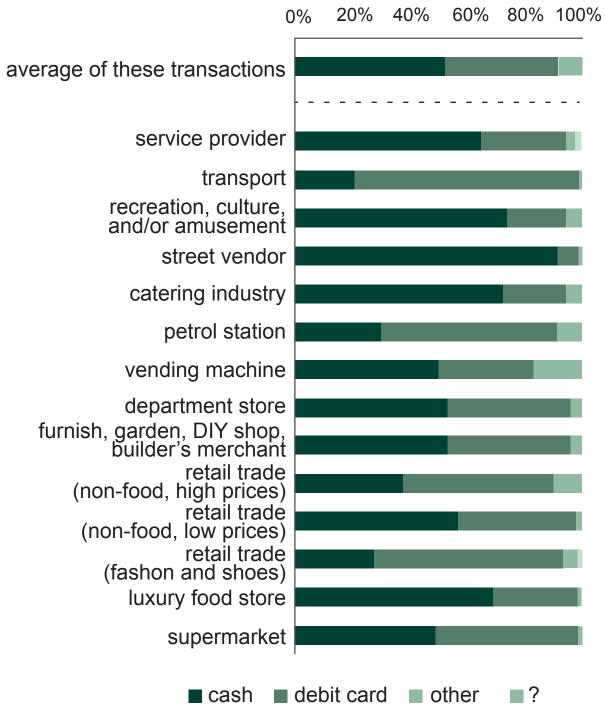
	< 20 euros	30 - 100 euros	200 - 1,000 euros	> 10,000 euros
Europe	87%	55%	20%	4%
Belgium	84%	48%	18%	5%
Germany	91%	69%	21%	4%
Spain	90%	64%	30%	6%
France	80%	15%	3%	0%
Italy	91%	77%	31%	4%
Luxembourg	77%	27%	10%	3%
Netherlands	65%	20%	8%	4%
Austria	82%	60%	29%	10%

Source: VU Amsterdam elaboration of ECB, 2011

Van der Cruijsen, Hernandez and Jonker (2015) measured whether the use of cash differs per sector in their study titled *In love with the debit card, but still married to cash*. Mainly street vendors, recreation and catering providers are paid in cash. The graph below shows the results of their study on payment methods in the Netherlands. Unfortunately, their study does not use the standard NACE business sector classification that we used in the IARM project and we could therefore not use their research results.

Figure 34 – Payment methods across Dutch business sectors

% per type of payment method on total payments. DNB/DPA payment survey. 2013



Source: VU Amsterdam elaboration of van der Cruijsen et al., 2015, p. 13

Cash-intensiveness across Dutch business sectors

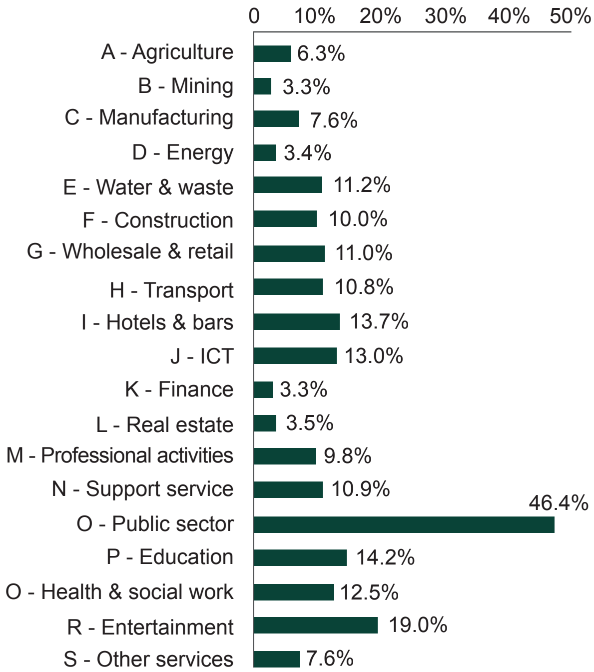
As stressed in Chapter 1, cash-intensive businesses are attractive to criminals because they ease the concealment and integration of illicit proceeds (FATF, 2010a; Gilmour & Ridley, 2015; Gilmour, 2014; Transcrime, 2013). But measuring the level of cash intensity at business sector level is not easy. The proxy adopted here is an indirect measure of the extent to which companies in a certain sector detain assets in cash: the **average cash/total assets ratio** of the companies operating in a certain sector. This proxy is preferred to other fundamental analysis ratios due to data availability and for other reasons.[59]

59. Other measures of liquidity are, for example, current assets / total assets or receivable days. It has been found that current assets / total assets is a meaningful proxy for cash intensiveness in Italy (see Chapter 2), but in the Netherlands the same patterns cannot be found (most of the evidence on current assets is limited to Italian mafias); we may therefore conclude that cash/total assets is a better proxy. Receivables days (or debtors days) measure the average length of time taken by a company's customers to pay their debts (O'Regan, 2006). It can be assumed that the lower the receivables days ratio, the more liquid the payments received by a company. Unfortunately, details on debtors and payables are not largely available in the source used for analysis (see also Chapter 2 and Annex).

The figure below shows this ratio in the various business sectors of the Dutch legitimate economy. Most striking is the **cash-intensiveness of the public sector** (which is not analysed in Italy because public bodies are not registered in the business register, while in the Netherlands they are). In the Netherlands the 'companies' that are registered in sector O (public sector) are public bodies of different governance levels (municipalities, provinces and water authorities can have their own 'company number'), police (regions), ministries, fire departments, and other institutions. It is not clear why these organisations would have such a high cash ratio according to our data (the same holds for the education sector, which, however, ranks high also in Italy).[60] Some other sectors do score high as expected, such as the **entertainment industry** (which includes **gambling, but also prostitution in the Netherlands)** and **hotels and bars**. These sectors are relatively popular for criminals to invest in (see e.g. Ferwerda & Unger, 2016; Kruisbergen et al., 2012; Levi, 2015). The cash-intensiveness may be among the factors explaining such high levels of criminal investments.
In terms of NACE divisions, those with the highest ratio of current assets are reported in the table below.

Figure 35 – Cash intensiveness in Dutch NACE sections

Cash/total assets (%). Last available year



Source: VU Amsterdam elaboration of BvD data

Table 27 – Cash/Total assets in Dutch sectors (%)
Top 10 NACE divisions. Last available year

BUSINESS SECTOR (NACE Divisions)	Cash/Total Assets
O 84. Public administration and defence; compulsory social security	46.4%
R 92. Gambling and betting activities	42.3%
N 79. Travel agency, tour operator reservation service and …	34.8%
R 90. Creative, arts and entertainment activities	25.2%
M 75. Veterinary activities	22.4%
H 53. Postal and courier activities	21.4%
E 37. Sewerage	19.9%
E 39. Remediation activities and other waste management services	19.7%
J 60. Programming and broadcasting activities	17.9%
C 26. Manufacture of computer, electronic and optical products	17.2%

Source: VU Amsterdam elaboration of BvD data

Once again, the division from sector O (public sector) is surprisingly high, while other divisions, such as gambling and betting activities (R 92) and Arts (R 90), have high cash intensity as expected.

60. One should consider that this can also be the result of the so-called 'denominator effect': It could be that the total of assets registered in the data is relatively low for these sectors, therefore giving the cash intensity measured as cash over total assets a high score.

Opacity of business ownership

As discussed in Chapter 1, complex and extensive corporate structures, especially if established in risky jurisdictions with low levels of financial transparency, are helpful for **concealing illicit flows and hiding beneficial ownership**. (see e.g. FATF, 2016b, 2014a; ECOLEF, 2013; Riccardi & Savona, 2013; de Willebois et al., 2011a; Blum et al., 1999; EBOCS Consortium, 2015; EURODAD, 2015; van Koningsveld, 2015).

The need for more detailed and **transparent information on business ownership** (in particular on beneficial owners – henceforth BO) has been stressed by FATF Recommendations (FATF, 2012) and then acknowledged at EU level in the updated version of the AML Directive (EU Directive 2015/849). However, problems of accessing data on ownership across different business registers and jurisdictions remain (Riccardi & Savona, 2013; EBOCS Consortium, 2015).

What is the level of ownership complexity of Dutch companies? To answer this question, IARM focuses on two sub-dimensions:

- The **complexity** of Dutch businesses' ownership structure as such (operationalised with the distance between the company and the beneficial owner – see below);
- The volume of business ownership connections with shareholders and BO from **risky jurisdictions**.

Level of complexity of Dutch businesses' ownership structure

Given available company data, measuring ownership complexity is not easy. Here it is assessed by considering the so-called **BO distance**, i.e. the average number of 'steps' which separate a company from its beneficial owner(s).[61]

Data on ownership of Dutch businesses is provided by **Bureau van Dijk** (hereafter BvD). Data on shareholders and beneficial owners for each Dutch company are collected, and are then aggregated by nationality of shareholder and beneficial owner (when available) for each business sector (NACE Rev. 2 classification) (see Annex for details). The analysis on the nationality of shareholders and beneficial owners covers 450,000 shareholders and 25,000 BOs.[62]

The proxies for opacity of business ownership should indicate the **dubious companies that have an unnecessarily complex ownership structure**. We therefore cannot rely on using only indicators of complexity, because bigger multinational companies have more complex ownership structures in general. For this reason, proxies are corrected (as in Italy and the UK, see Chapters 2 and 4) by weighting the BO distance by a measure of company size (specifically, the average total assets). To illustrate this, the figures below shows the (unweighted) average BO distance and the average company size. Figure 38 shows instead how the average BO distance per sector changes when corrected (or weighted) by average company size (fig. 38).

A business sector like agriculture is characterised by direct ownership, since its average BO distance is close to one (a BO distance of 1 means direct ownership). The sectors where the average BO distance is highest are Mining, Finance and Energy, all characterised by a high number of multinational companies and FDI (fig. 36).

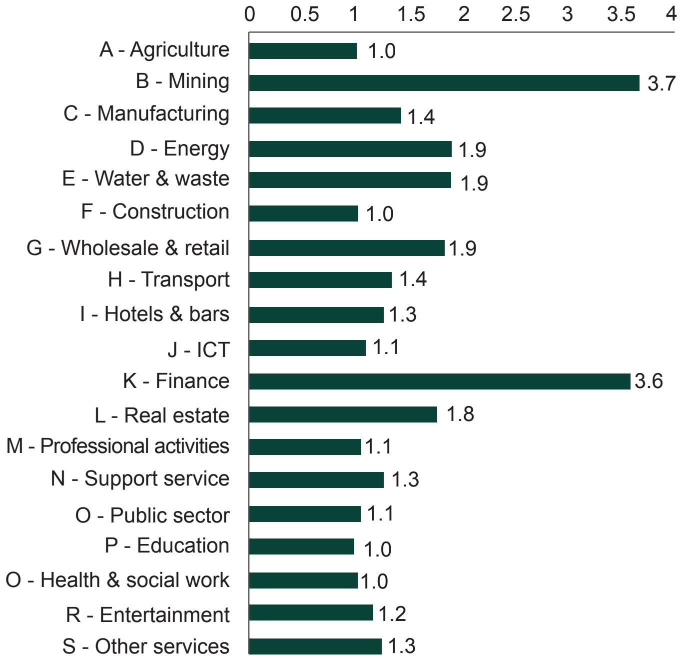
Turning to the average company size, exactly those sectors with the highest BO distance are those characterised by, on average, the biggest companies (highest average total assets). This indicates that, as expected, largest companies, like multinationals, have on average a more complex ownership structure. Therefore, the BO distance indicator is corrected for average company size to gain **a better proxy for unnecessarily complex ownership structures**. The graph below shows the results after weighting the BO distance (and normalising to scale 0-100) (fig. 38).

61. Beneficial owners in the BVD definition refer to owners who, in the ownership chain, hold directly or indirectly a minimum 10% at the first level of a company and 10% at further levels of control (see Annex for details). When BO distance equals 1, the company is directly controlled by its BO(s) (see Annex for details).

62. Initially, also the % of foreign owners of businesses in each sector was considered as a proxy for ML vulnerability, because the higher the number of foreign shareholders, the more difficult it is to trace the beneficial ownership and therefore the higher the risk. However, this variable would overlap to a large extent (correlation of 0.97) with the number of shareholders and BOs from risky jurisdictions (see below). Therefore, it was decided not to include it.

Figure 36 – Average BO distance per business sector

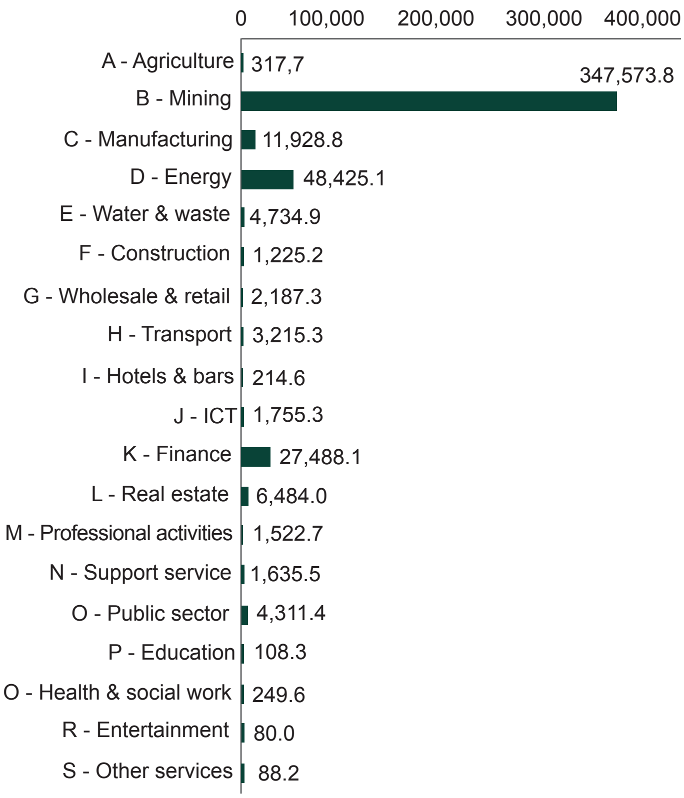
NACE sections. Last available year



Source: VU Amsterdam elaboration of BvD data

Figure 37 – Average company size (total assets) per business sector

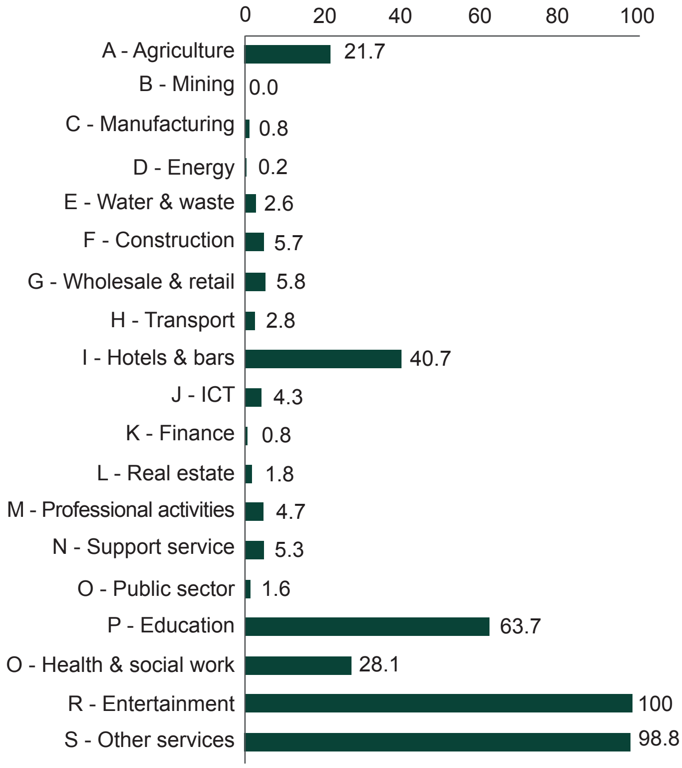
Average total assets in thousands of euros. NACE sections. Last available year



Source: VU Amsterdam elaboration of BvD data

Figure 38 – Average BO distance per business sector

Normalised to scale 0-100. NACE sections. Weighted by average company size



Source: VU Amsterdam elaboration of BvD data

Weighting the BO distance by company size shows that the highest levels of 'unexplained opacity' are in divisions such as entertainment (R), other services (S) and hotels and bars (I).[63] For the same reason, the correction by average company size is also applied to other measurements of opacity – shareholders' risk score and BOs' risk score.

Business ownership connections with risky jurisdictions

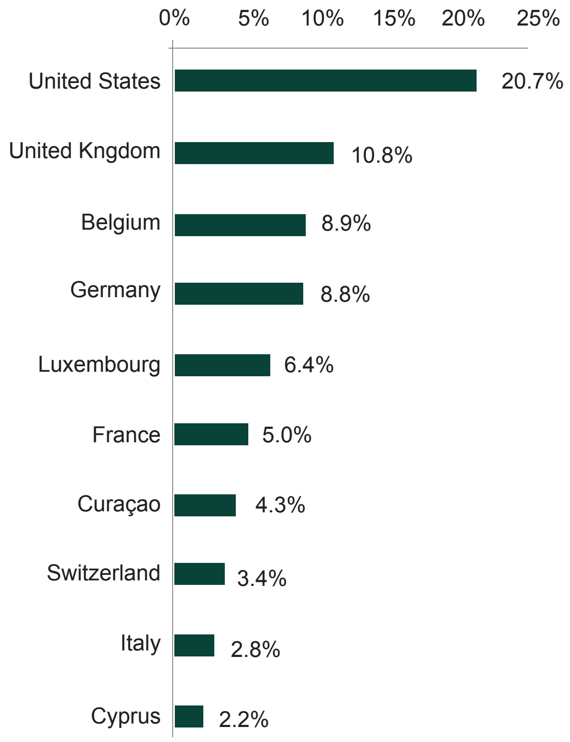
Foreign shareholders represent 7.8% of the total number of shareholders in the Netherlands. This is higher than for instance in Italy (see Chapter 2), indicating that the Netherlands is a relatively open economy with a high number of foreign investors. The table below shows the top 10 origins of foreign shareholders of Dutch companies. The list consists of the big **Western economies, neighbouring countries** and a Caribbean island which is part of the Kingdom of the Netherlands (**Curaçao**). The only exception is

63. A disadvantage of this correction is that the unit of measurement of the statistic becomes harder to interpret.

Cyprus, in place 10, which might have to do with relations between the offshore businesses that are based in Cyprus but have mailbox companies based in the Netherlands. Data seem to confirm that the share of foreign owners from certain countries can reflect (see Ferwerda & Riccardi, 2016):

- geographical proximity (e.g. shareholders from Belgium and Germany);
- volume of FDI and trade exchanges (e.g. United States);
- foreign citizens resident in The Netherlands and former cultural/political links (e.g. Curaçao);
- tax incentives (e.g. Luxembourg, Cyprus);
- reasons related to lack of transparency of certain foreign jurisdictions (see below).

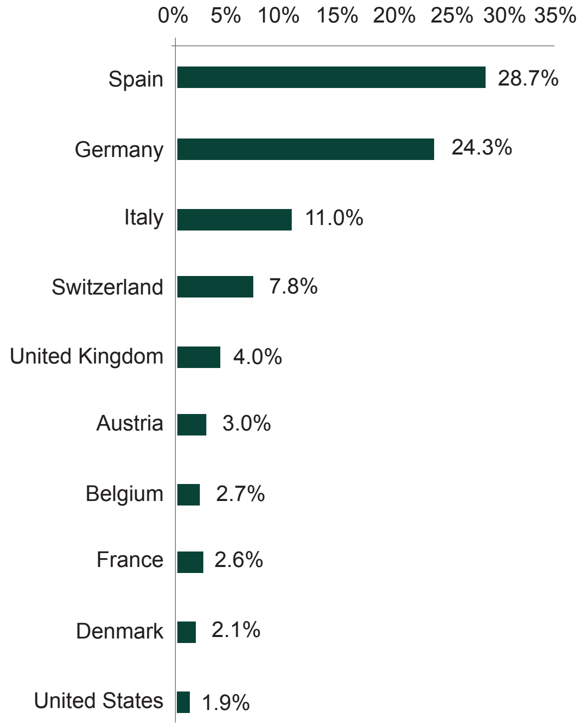
Figure 39 – Most prevalent foreign shareholders of Dutch companies (%)



Source: VU Amsterdam elaboration of BvD data

In terms of **beneficial owners**, the top 10 list is slightly different.

Figure 40 – Most prevalent foreign beneficial owners of Dutch companies (%)



Source: VU Amsterdam elaboration of BvD data

This list consists of European countries (except the US in place 10). This strengthens the intuition that geographical proximity is a factor more important to explain foreign beneficial ownership than to explain foreign shareholders. Spain ranks on top – as also in Italy and the UK. The reason is not very clear and would deserve further investigation (see Section 2.3 for some interpretations on Italian data).

At **NACE division level**, the industries with the highest percentages of **foreign owners** are: C 19 Manufacture of coke and refined petroleum products (33%), B 08 Other mining and quarrying (25%), and B 06 Extraction of crude petroleum and natural gas (18%). Since these are industries with multinational companies, this might not be very surprising. More interesting is when we correct the percentage of foreign shareholders for average company size (as illustrated above for BO distance).

Table 28 – Foreign Beneficial Owners by business sector weighted by average company size

Top 10 business divisions. Last available year.

Rank	NACE division
1	N 80. Security and investigation activities
2	I 55. Accommodation
3	G 47. Retail trade, except of motor vehicles and motorcycles
4	N 79. Travel agency, tour operator reservation service and related activities
5	S 95. Repair of computers and personal and household goods
6	R 91. Libraries, archives, museums and other cultural activities
7	N 78. Employment activities
8	S 96. Other personal service activities
9	C 18. Printing and reproduction of recorded media
10	I 56. Food and beverage service activities

Source: VU Amsterdam elaboration of BvD data

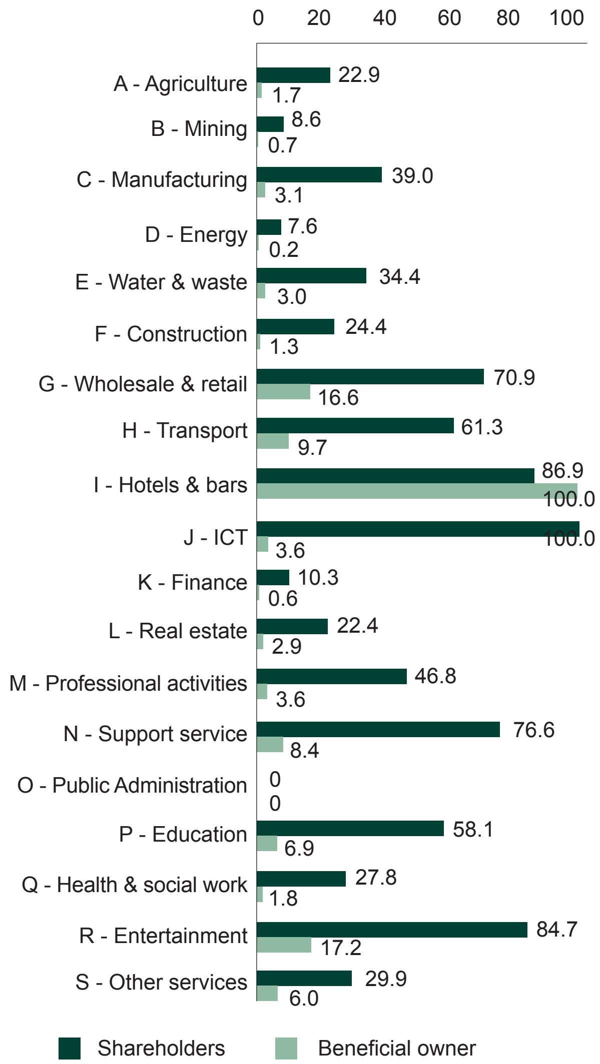
Clearly, the business sectors with the highest percentage of foreign owners are not simply the big multinational industries when corrected for company size. We now see some sectors that are generally more international in nature (such as **hotels (I 55), restaurants (I 56) and travel (N 79)**) and not the agriculture, mining and manufacturing sectors.[64] Still, this poses the question of whether simply foreign ownership is a good indicator of money laundering risk. It might be necessary to go more into detail about where the shareholders specifically come from.

Not all foreign nationalities in fact encompass the same ML risk. A variety of jurisdictions exist which use **financial and corporate secrecy** to attract legitimate and illicit financial flows (Tax Justice Network, 2015b). In order to measure the extent of Dutch businesses' ownership links with these risky jurisdictions, the % of foreign shareholders and BOs in each business sector is multiplied by an **indicator of opacity and low transparency** (the **Secrecy Score** of the **FSI - Financial Secrecy Index, FSS**).[65] This approach is used also in previous studies (e.g. Cassetta, Pauselli, Rizzica, & Tonello, 2014; Gara & De Franceschis, 2015; Riccardi, Milani, et al., 2016). In particular, each nationality of shareholders and BO is weighted by the relevant value of the FSS, and corrected with a measure of company size in order to offset the incidence of multinational companies (the same method is used in the analyses of Italy and UK – see Chapters 2, 4, 5 and Annex for details).

64. Though in the NACE classification printing and reproduction of recorded media is classified as a type of manufacturing.

65. The Secrecy Score is a component of the Financial Secrecy Index (FSI) developed by the Tax Justice Network and issued every 2 years. The secrecy score is a composite indicator which evaluates different dimensions of secrecy in the financial sector and in the legislation of selected jurisdictions. In particular, it evaluates: A) the level of banking secrecy; B) access to beneficial ownership information; C) corporate transparency; D) efficiency of tax and financial regulation; E) compliance with international standards; F) international cooperation (Tax Justice Network, 2015). For further details see Annex. The secrecy score has been preferred to other measures of risky jurisdictions (e.g. international or national blacklists) because of its independency and transparency of the evaluation methodology.

Figure 41 – Level of risky ownership connections with risky jurisdictions
Normalised to scale 0-100. NACE sections. Weighted by average company size



Source: VU Amsterdam elaboration of BvD and TJN data

In terms of opacity of shareholders, the business section information and communication technologies (ICT) scores surprisingly high. When looking at more detailed data (at division level), it seems that this result is mainly driven by the division **J 63 (Information service activities) and J 62 (Computer programming activities)**. a sector where (at least for the companies on which we have data) the majority of shareholders are foreign. Also **section I (Accommodation) and R (Entertainment)** rank high in terms of opacity of shareholders. As expected, the lowest opacity is found in the public sector.

The **hotel and bar sector (Section I) has the highest opacity for beneficial owners**, when corrected for company size. Although one can imagine that this sector is more international in nature, the extent to which it stands out is surprising. Most foreign beneficial owners in this sector come **from Luxembourg and Italy**. Italy is not unexpected, given the abundance of Italian restaurants in the Netherlands, but the amount of beneficial owners from Luxembourg seems more related to tax planning than to food tradition.[66] As expected, the public sector has no opacity at all in terms of beneficial owners.

Business profitability

According to some scholars, profitable sectors may be more prone to ML because the goal is to create 'white' profits and because upcoming markets, with increasing profit opportunities and where the regulations are still in development are interesting for criminals (see Chapter 1 for details). To measure sectors' profitability, average **gross profit (data from BvD) is divided by the total turnover**. To make sure that accounting and taxation differences between sectors do not skew our results, the standard EBITDA margin[67] measurement for gross profit is preferred.

The most profitable sector in the Netherlands, according to our BvD data, is health and social work (section Q). We do not see upcoming industries (such as renewable energies) in this top 10, although they are mentioned in the literature as specifically prone to criminal investments (see e.g. Caneppele, Riccardi, & Standridge, 2013). Other sectors which are generally considered at high profit margin, like energy or IT, do not appear in this ranking. The reason may be due to the use of the EBITDA margin ratio instead of other return on investment ratios like ROE or ROA (for which there is some problem of data availability and reliability).

In truth, some scholars also question a direct relationship between profitability and money laundering (see Chapters 1 and 2). In the IARM analysis of Italy, for example, two models at business sector level are presented, one including profitability and one excluding it. The sensitivity analysis (see step 7) shows that excluding profitability from the analysis does not alter the results significantly for the Netherlands.

66. It should also be noted that the amount of BOs in the BvD data is sometimes relatively low for certain Dutch sectors, which possibly increases the variance of the data.

67. EBITDA stands for Earnings Before Interest, Taxes, Depreciation and Amortization. EBITDA margin is here calculated as the ratio between EBITDA and turnover.

Table 29 – Most profitable Dutch sectors (%)
NACE divisions. Last available year

NACE division	Average EBITDA margin (%)
Q 87. Residential care activities	63%
Q 88. Social work activities without accommodation	45%
Q 86. Human health activities	33%
P 85. Education	30%
E 39. Remediation activities and other waste management services	21%
N 77. Rental and leasing activities	20%
C 11. Manufacture of beverages	20%
A 03. Fishing and aquaculture	16%
J 58. Publishing activities	16%
E 37. Sewerage	15%

Source: VU Amsterdam elaboration of BvD data

STEP 3 – DATA COLLECTION AND NORMALISATION

Data collection, cleaning, imputation of missing value, validation

For each identified proxy variable, **data are collected** from the relevant sources. When not publicly available, information was requested from the relevant authority, institution or data provider. Due to a lack of data availability, different variables are covered with different time spans (see Annex for details).

The number of companies in the various business sectors in the Netherlands varies greatly. We use relative values to make sure that this does not influence the PCA; but to prevent outliers and missing variables, those business sectors that include on average fewer than 10 registered companies according to the company data from the Statistics Bureau Netherlands (CBS) in the quartiles of 2014 and 2015 were excluded from the dataset. This means that **four sectors (NACE divisions) were removed**: B 05 Mining of coal and lignite, T 97 Activities of households as employers of domestic personnel, T 98 Undifferentiated goods- and services-producing activities of private households for own use, and U 99 Activities of extraterritorial organisations and bodies. As a result, ML risk is assessed across **83 NACE divisions** of the Dutch legal economy.

Data transformation and normalisation

The IARM methodological approach relies on the **concept of *relative risk*** (see Chapters 1 and 2), which means that the money laundering threats or vulnerabilities should be weighted for the size of the business sector if the risk factors are not yet a relative measure (such as cash intensity or profitability). Therefore these variables are transformed into **ratios on relevant control variables** (e.g. number of companies or total assets).[68] Consequently, a min-max normalisation is applied, making all values between 0 and 1, with 0 for the lowest relative value and 1 for the highest.[69]

68. As an example, data on OC investments (from the OC monitor as well as from the EU-project OCP) list the number of OC investments divided by the number of companies in each sector. Otherwise if OC investments were randomly distributed across sectors the bigger sectors would have more investments, falsely indicating more risk.

69. This min-max normalisation is done with the following formula: Normalised value = (value – lowest value of proxy) / (highest value of proxy – lowest value of proxy). Using other normalisation methods do not alter the results significantly.

STEP 4 – DATA EXPLORATION AND CORRELATION ANALYSIS

First, the distribution of variables is explored (through descriptive statistics and basic inference tests) to identify specific data patterns. To provide an overview of the interdependence of the variables – and to test whether the overlap of variables is not too strong – the **linear Pearson correlation** is calculated (see corrplot below).

The table shows that the correlations between the variables are not particularly strong if compared, for instance, with the regional analysis of Italy. Although the correlations between the different proxies for organised crime investments are relatively high, the correlation among vulnerability proxies are much lower. This indicates that the **power of explanation of ML risk should come from the combination of all these factors**. The correlations show that variables do not measure exactly the same thing. It is decided not to let the correlation be a decisive factor for inclusion of variables, because a good external variable is not available to test the usefulness of inclusion (contrary to the regional analysis in Italy – see Chapter 2).

Table 30 – Correlation matrix of the variables used in the PCA

Variables	1	2	3	4	5	6	7	8	9
1. OC infiltration OCM	**1.00**								
2. OC infiltration OCP	0.21	**1.00**							
3. Administrative denials	**0.28***	**0.72***	**1.00**						
4. Corporate tax anomalies	-0.16	-0.04	0.02	**1.00**					
5. Cash intensity	-0.14	0.21	0.18	0.17	**1.00**				
6. BO distance	-0.07	-0.06	0.01	0.17	**0.24***	**1.00**			
7. Shareholders' risk score	-0.06	-0.10	-0.05	0.13	**0.24***	**0.37***	**1.00**		
8. BOs' risk score	0.17	**0.25***	**0.42***	0.08	0.12	0.15	**0.50***	**1.00**	
9. Profitability	-0.19	-0.08	-0.02	0.02	0.03	0.09	-0.14	-0.09	**1.00**

**values are different from 0 with a significance level alpha of 0.05.*

Source: VU Amsterdam elaboration

STEP 5 - PRINCIPAL COMPONENT ANALYSIS (PCA)

To develop the composite indicator of ML risk, a **principal component analysis (PCA)** approach is adopted.[70] This approach helps to downsize the number of variables into a smaller number of components (Kabacoff, 2015; OECD & JRC, 2008; Jolliffe, 2002; Rencher, 2002), which would correspond to sub-dimensions of ML risk. The PCA is carried out as follows:

1. The **number of principal components** (PC) is selected on the basis of generally accepted standards such as the so-called Kaiser-Harris criterion (see Kabacoff, 2015; Jolliffe, 2002; OECD & JRC, 2008);
2. The three extracted principal components are **identified, 'labelled' and discussed**;
3. Principal components are then aggregated using **non-discretionary weights** extracted from the PCA to construct the final composite indicator (see STEP 6).

The results of the PCA are summarised in table 31.

70. Principal component analysis is a multivariate data analysis technique used, in a similar way to other approaches (e.g. factor analysis), to reduce the information contained in large datasets into a smaller number of components (or factors, in factor analysis), each of them able to summarise a specific phenomenon explained by a range of correlated variables. For this purpose, PCA uses an orthogonal transformation of the correlated variables into a set of principal components which are uncorrelated with each other. Specifically in the analysis of ML risk in the Netherlands, a Pearson (n) principal component analysis with varimax rotation is performed. See also Chapter 1 and Annex for details.

Table 31 – Relevant components calculated with principal component analysis

	PC1	PC2	PC3
OC infiltration OCM	0.35	0.04	-0.64
OC infiltration OCP	0.89	-0.07	-0.02
Administrative denials	0.92	0.06	-0.02
Corporate tax anomalies	0.00	0.25	0.47
Cash intensity	0.31	0.31	0.55
BO distance	-0.05	0.55	0.39
Shareholders' risk score	-0.11	0.89	0.03
BOs' risk score	0.42	0.68	-0.16
Profitability	0.01	-0.31	0.59
Eigenvalue	2.22	1.83	1.26
Variability (%)	24.62	20.35	14.02
Cumulative %	24.62	44.97	58.99

Source: VU Amsterdam elaboration

* the selected principal components (with an eigenvalue > 1) are shown

Three principal components are selected[71], which together explain about 60% of the variability. For each of the principal components we highlight the variables with a non-discretionary weight of more than 0.5 (and those between 0.3 and 0.5 with a lighter colour). Based on these, the four principal components are labelled[72] as follows:

- PC1 – OC infiltration and BO secrecy
- PC2 – Opacity of business ownership
- PC3 – Cooking the books

The PCA shows that the risk factors on the threat of organised crime investments are distinct from those on the threat of corporate tax anomalies in the sense that they do not appear in the same components. The combination of **OC infiltration threat with beneficial ownership secrecy** is shown to be the main component of money laundering risk.

Opacity in the corporate structure is indicated as the second most important component of money laundering risk. The third component of ML risk points to cash intensive and profitable companies with tax anomalies. We label this component 'cooking the books'. Interestingly, this component is negatively related to OC investments (based on Organised Crime Monitor data), indicating that the sectors related to cooking the books are not the same in which the police more often find organised crime investments. This cooking the books component could refer to a very traditional method of money laundering, i.e. adding cash to the register (see e.g. Ferwerda, 2012).

Adding cash to the register is a) harder to detect in cash-intensive sectors, b) creates extra profits, and c) creates a difference between the actual business of the company and its financial statements which can be labelled a tax anomaly when detected. This PCA may therefore encompass **different money laundering aspects**, *modi operandi* or typologies.

Although we are eventually interested in the overall ML risk per sector, it is interesting to gain some insights into how these different risk components vary across sectors.

71. All the principal components with eigenvalue above 1 are selected, in line with Kaiser (1960).

72. Note that these labels are the interpretation of the researchers. We cannot prove claims like 'cooking the books'; we merely have indicators that on average indicate the phenomenon at relatively higher proportions in some sectors rather than others.

Table 32 – Top 10 sectors for each principal component

PC1 – OC infiltration and BO secrecy	PC2 – Opacity of business ownership	PC3 – Cooking the books
I 55. Accommodation	N 80. Security and investigation activities	Q 87. Residential care activities
R 92. Gambling and betting	S 95. Repair of computers and personal ...	R 90. Creative, arts and entertain-ment
H 51. Air transport	R 90. Creative, arts and entertainment	Q 88. Social work activities ...
I 56. Food and beverage service	N 79. Travel agency, tour operator ...	R 92. Gambling and betting
E 38. Waste collection, treatment …	S 96. Other personal service activities	O 84. Public administration and defence..
C 23. Manufacture of other non-metallic ..	N 81. Services to buildings and landscape..	Q 86. Human health
G 47. Retail trade, except motor vehicles..	C 31. Manufacture of furniture	P 85. Education
O 84. Public administration and de-fence..	J 63. Information service activities	E 39. Remediation activities and other..
N 80. Security and investigation	G 47. Retail trade, except motor vehicles ..	A 01. Crop and animal production, hunting
N 79. Travel agency, tour operator …	M 74. professional, scientific and technical..	R 93. Sports, amusement and recreation

Source: VU Amsterdam elaboration

Once again, the results seem to indicate that the extracted principal components capture different aspects of ML risk: **there is not a single sector that appears in the top 10 of each component**. The most important PC – OC infiltration and BO secrecy – has, as expected, in its top 10 many sectors that are also mentioned in the literature on OC investments in the Netherlands (Ferwerda & Unger, 2016; Kruisbergen et al., 2012) but also some unexpected ones (such as C 23 Manufacture of other non-metallic mineral products – which however is related to the extraction and treatment of cement, which is a crucial step in the building industry - and O 84 Public administration and defence; compulsory social security). For the other PCs we have less knowledge on what the expected sectors would be. It is remarkable that the arts sector (R 90) scores high for both principal component 2 and 3, indicating that the arts sector consists of relatively profitable and cash-intensive businesses with more tax anomalies and more opacity.

STEP 6 – AGGREGATION AND COMPOSITE INDICATOR CONSTRUCTION

The principal components, identified through the PCA, can then be combined in order to construct a synthetic composite indicator of ML risk. To do so, they are **aggregated using as weight the proportion of variance** (of the model) explained by each component, and then normalised to the **scale 0-100** according to a min-max criterion, where 100 = highest ML risk.[73] In other words (see Annex for details):

$$\textit{ML RISK COMPOSITE INDICATOR}_i = \sum_{j=1}^{J} (S_{ij} \times w_j) = (S_{i1} \times w_1) + (S_{i2} \times w_2) + (S_{i3} \times w_3)$$

where i = 1, ..,I business sectors (in this case I = 83), j = 1, … , J component (in our case J = 3) and w_j = proportion of variance (out of the total variance explained by the model) explained by each of the three components. Sij is the relevant value extracted by the PCA for each sector and for each component. The composite score is normalised on a 0-100 scale (where 100 = highest risk).[74]

The table below presents the **top 10 business sectors** ranked according to the overall ML risk. The **gambling sector (R 92)** scores the highest in our ML risk calculations. Casinos (and other gambling and gaming businesses, including video lottery and slot-machine rooms) fall under (inter)national anti-money laundering regulations, which means that they have to report unusual transactions and identify their customers. Even though this was not an obligation under the third AML directive, many countries in the EU have extended these requirements to other gaming and gambling activities, because these activities are considered to bear a certain risk of money laundering (Unger, Ferwerda, Broek, & Deleanu, 2014, p. 23). The vulnerability of casinos to money laundering was recognised in the revision of the FATF 40 Recommendations, with obligations on casinos being significantly enhanced, and further acknowledged in the fourth EU AML directive. To back this up, the FATF published a report on these vulnerabilities of casinos and gaming sector (see FATF, 2009).

The sector ranking second is **accommodation, i.e. hotels (I 55)**. This is not surprising considering some recent literature and evidence (see e.g. Emergo, 2011 for a study on the relation between crime and hotels in the Netherlands, more specifically in Amsterdam).

Third on the list is the **art and entertainment sector (R 90)**. Arnoud Boot indicated already in 1994 that the art sector is almost perfect for money laundering, because it is one of the only sectors with a duty of confidentiality (see Boot & Wolde, 1997, p. 32). This is confirmed by the fact that the art sector scores high on business ownership opacity (see STEP 5), although Boot refers to the confidentiality of the customers, while our principal component 2 refers to the 'confidentiality' (or opacity) of owners. Sector **R 93 - Sports activities and amusement and recreation activities**, which includes also prostitution services, is slightly lower in the list.

The business sector of **security and investigation agencies (N 80)** is fourth on our ML risk index. There have been several indications that outlaw motorcycle gangs are active in this sector (e.g. KLPD, 2014, pp. 30, 34, 44, 66). Further down the list is another business sector that has been mentioned in studies on money laundering cases in the Netherlands: **bars and restaurants** (see e.g. Ferwerda, 2012; Emergo, 2011; Savona & Riccardi, 2015).

See Annex for an analysis of whence the composite risk derives (which principal components) for these top 10 sectors. As could be seen already at STEP 5, the sector with the highest risk – gambling – scores high in terms of OC infiltration as well as cooking the books indicators. Accommodation mainly scores high on OC infiltration, and the art sector scores high on opacity and cooking the books.

73. The choice of using the proportion of variance as weight for components' combination makes it possible to address the weakness of most composite indicators currently available in the literature, i.e. the fact that factors are aggregated attributing almost discretionary weights which heavily impact on the final result and ranking. In this case the weight of each component is the one resulting from the statistical analysis.

74. Risk score = (Composite score – lowest Composite score) / (highest Composite score – lowest Composite score) x 100

The **10 least risky sectors** are shown in the table below. Sectors which do not directly deal with customers seem to score low (such as manufacturing, warehousing, fishing and logging). A further analysis of the results shows that many **manufacturing sectors** are among the least risky sectors (ten divisions of C section have a risk score below twenty). High barriers to entry, high capitalisations, and the requirement of high (technical and human) skills **might not be appealing to criminals wanting to launder their money**. This result is in line with what found in Italy, where also manufacturing scores low (see Chapter 2).

A result that may be somewhat surprising is that **insurance and financial sectors** (K 65 and K 64) have a low ML risk. Both are among the regulated sectors under the AML policy regime. It cannot be determined whether these regulations are targeted on the wrong sectors or whether the AML efforts have been successful in lowering the money laundering risk in these industries. A third – and more likely – explanation could be that the money laundering *modi operandi* which are most relevant and frequent for this sector are not captured by the proxies of this analysis. The same could be said as regards sectors like **real estate** agencies (NACE Section L) and **trust and company service providers** which, despite being pointed out by the literature as vulnerable to money laundering, do not rank among the most risky business sectors.

Table 33 – Business sectors in the Netherlands with the highest money laundering risk

Top 10 NACE divisions according to ML risk composite indicator

Sector	ML composite indicator
R 92. Gambling and betting activities	100.0
I 55. Accommodation	97.9
R 90. Creative, arts and entertainment activities	72.9
N 80. Security and investigation activities	69.8
S 95. Repair of computers and personal and household goods	54,4
N 79. Travel agency, tour operator reservation service and related activities	54.1
S 96. Other personal service activities	48.7
O 84. Public administration and defence; compulsory social security	46.6
R 93. Sports activities and amusement and recreation activities	44.0
I 56. Food and beverage service activities	43.8

Source: VU Amsterdam elaboration

Table 34 – Business sectors in the Netherlands with the lowest money laundering risk

Least 10 NACE divisions according to ML risk composite indicator

	ML composite indicator
C 20. Manufacture of chemicals and chemical products	10.7
C 11. Manufacture of beverages	10.3
A 03. Fishing and aquaculture	9.9
H 52. Warehousing and support activities for transportation	9.8
A 02. Forestry and logging	5.8
C 33. Repair and installation of machinery and equipment	5.0
K 64. Financial service activities, except insurance and pension funding	4.8
C 19. Manufacture of coke and refined petroleum products	3.2
K 65. Insurance, reinsurance and pension funding, excl. compulsory social security	1.0
C 12. Manufacture of tobacco products	0.0

Source: VU Amsterdam elaboration

STEP 7 – SENSITIVITY ANALYSIS AND VALIDATION

In the Netherlands, no good alternative external measure of money laundering risk is available as it is among Italian provinces (where the ML risk indicator is compared to STRs distribution, see Chapter 2). Therefore the validation of the robustness of the results is carried out at three levels:

a) Testing the extent to which the results are driven by using a PCA. To do so, the results of the PCA are **compared against a theoretical model** in which the various (normalised) proxy variables for ML risk factors, based on the literature (see STEP 1), are simply combined together without any further statistical elaboration.

b) Testing the extent to which the results are driven by the selection of variables. To do so, **proxy variables are dropped, one-by-one, from the PCA model**. This produces nine new composite scores which are compared with the baseline model presented in STEP 6.

c) Testing to the extent to which the results are driven by **specific methodological choices adopted in the PCA process**, such as normalisation techniques, varimax rotation and weighting of the principal components.

Comparison with a theoretical model

Instead of using a PCA approach, one can also simply assume that all the different risk factors (or proxy variables) that are mentioned in the literature are equally important. By applying this simple theoretical approach and comparing its results with our PCA method, we try to determine whether our results are driven by the PCA itself or whether a theoretical approach would confirm our results. To calculate the ML risk for our more theoretical approach with equal weights, we apply the following formula:

$$ML\ RISK\ COMPOSITE\ INDICATOR_i = \sum_{j=1}^{J}(proxy\ variable_{ij})$$

where i = 1, ..,I are the business sectors (in this case I = 83) and j = 1, … , J are the (normalised) proxy variables for risk factors (in our case J = 9). The composite scores are then normalised to the 0-100 scale in the same way done for the PCA approach (see the former step for the exact formula used).

Below, the top 10 and bottom 10 business sectors stemming from the PCA and the theoretical approach are listed and compared side by side.

Table 35 – Business sectors in the Netherlands with the highest money laundering risk
Top 10 NACE divisions. PCA approach (left) vs. theoretical model (right)

PCA approach - Sector		Theoretical model - Sector	
R 92. Gambling and betting activities	100.0	I 55. Accommodation	100.0
I 55. Accommodation	97.9	N 80. Security and investigation activities	77.6
R 90. Creative, arts and entertainment activities	73.0	R 92. Gambling and betting activities	77.0
N 80. Security and investigation activities	69.8	R 90. Creative, arts and entertainment activities	67.4
S 95. Repair of computers and personal and household goods	54.4	I 56. Food and beverage service activities	59.2
N 79. Travel agency, tour operator reservation service ...	54.1	S 95. Repair of computers and personal and ...	56.3
S 96. Other personal service activities	48.7	G 47. Retail trade, except of motor vehicles and ...	52.7
O 84. Public administration and defence; ...	46.6	H 53. Postal and courier activities	50.9
R 93. Sports activities and amusement and recreation ..	44.0	N 81. Services to buildings and landscape ...	47.7
I 56. Food and beverage service activities	43.8	S 96. Other personal service activities	47.0

Source: VU Amsterdam elaboration

Table 36 – Business sectors in the Netherlands with the lowest money laundering risk

Lowest 10 NACE divisions. PCA approach (left) vs theoretical model (right)

PCA approach - Sector		Theoretical model - Sector	
C 20. Manufacture of chemicals and chemical products	10.7	E 36. Water collection, treatment and supply	14.3
C 11. Manufacture of beverages	10.3	D 35. Electricity, gas, steam and air conditioning ...	14.2
A 03. Fishing and aquaculture	9.9	C 11. Manufacture of beverages	13.8
H 52. Warehousing and support activities for transportation	9.8	B 09. Mining support service activities	13.4
A 02. Forestry and logging	5.8	C 20. Manufacture of chemicals and chemical ...	12.6
C 33. Repair and installation of machinery and equipment	5.0	A 03. Fishing and aquaculture	8.2
K 64. Financial service activities, excl insurance and pension	4.8	C 33. Repair and installation of machinery and ...	4.9
C 19. Manufacture of coke and refined petroleum products	3.2	C 19. Manufacture of coke and refined petroleum ...	3.1
K 65. Insurance, reinsurance and pension funding, excl ...	1.0	A 02. Forestry and logging	2.2
C 12. Manufacture of tobacco products	0.0	C 12. Manufacture of tobacco products	0.0

Source: VU Amsterdam elaboration

According to the theoretical model, the hotel sector appears as the most risky. The table above shows that 7 out of the top 10 sectors are the same across the two approaches, although the ranking is slightly different in some cases. The **correlation between the two risk scores is 0.9**. Also after testing other ways to add up the variables,[75] the results are very similar. Because of this high correlation, it can be deduced that PCA is not the 'driving force' of the specific risk scores. The results are therefore quite robust to the model specification.

Robustness with respect to the selected variables

A sensitivity analysis is carried out by **dropping one variable at a time** to check the sensitivity of the results with respect to variables' selection. This means that nine alternative ML composite risk scores are calculated and compared with the original ('complete') model including all nine proxy variables (as presented at STEP 6). The table below shows all the correlations between this model and the others. The minimum is r = 0.92, denoting again that the results are robust even after controlling for the influence of variables' identification.

Table 37 – Correlations between the final model and others where one variable is dropped at a time

	1	2	3	4	5	6	7	8	9	10
1. Complete model	**1.00**									
2. no OC infiltration OCM	**0.99**	**1.00**								
3. no OC infiltration OCP	**0.97**	**0.96**	**1.00**							
4. no administrative denials	**0.95**	**0.93**	**0.95**	**1.00**						
5. no corporate tax anomalies	**0.98**	**0.96**	**0.94**	**0.93**	**1.00**					
6. no cash intensity	**0.93**	**0.93**	**0.92**	**0.85**	**0.90**	**1.00**				
7. no BO distance	**0.97**	**0.96**	**0.92**	**0.92**	**0.94**	**0.89**	**1.00**			
8. no shareholders' risk	**0.92**	**0.86**	**0.86**	**0.83**	**0.93**	**0.87**	**0.89**	**1.00**		
9. no BOs' risk	**0.94**	**0.88**	**0.89**	**0.90**	**0.93**	**0.87**	**0.90**	**0.97**	**1.00**	
10. no profitability	**0.99**	**0.99**	**0.94**	**0.94**	**0.96**	**0.91**	**0.98**	**0.87**	**0.90**	**1.00**

*all values different from 0 at 0.05 level

Source: VU Amsterdam elaboration

75. For example, one can first make a score for the threat variables (by adding them up and dividing by the number of threat variables) and adding them to a score for the vulnerability variables (by adding them up and dividing by the number of vulnerability variables). Similarly, the opacity proxies can be split from the other vulnerabilities to calculate separate scores and add them to a score for the threat variables.

Robustness with respect to specific methodological choices

To test the sensitivity of the model with respect to changes in the parameters adopted in the statistical analysis (e.g. weighting, rotation, normalisation), alternative models are calculated, looking at how the results change depending on the adoption of other criteria. Four alternative choices are tested (see also what done in Italy and the UK – Chapters 2 and 4 – and see Annex):

- **Rotation**: using an Oblimin rotation (O) instead of a Varimax rotation (V)
- **Weighting**: equal weights (E) instead of weights based on the proportion of variance explained (P)
- **Aggregation**: Weighted arithmetic mean (S)
- **Standardisation of the components**: standardisation or Z-scores (T) instead of Min-Max normalisation (D)
- **Standardisation of the final indicator**: standardisation or Z-scores (Z) instead of Min-Max normalisation (M)

Since these 4 choices are independent of each other, 15 alternative PCAs are calculated – besides the original model that we applied in STEP 6 (MODEL VPSTM) and the theoretical model that is presented in the beginning of STEP 7. We code these models based on the capital letters that are shown in brackets above. This sensitivity analysis shows that these methodological choices made in IARM do not significantly affect the results. The correlation matrix below indicates clearly that virtually the same results are found when different (combinations of) choices are made.

Table 38 – Correlations among ML risk composite indicators after applying different methodological options

	VP STM	*VP STZ*	*VP SDM*	*VP SDZ*	*VE STM*	*VE STZ*	*VE SDM*	*VE SDZ*	*OP STM*	*OP STZ*	*OP SDM*	*OP SDZ*	*OE STM*	*OE STZ*	*OE SDM*	*OE SDZ*
VPSTM	**1.00**															
VPSTZ	**1.00**	**1.00**														
VPSDM	**0.99**	**0.99**	**1.00**													
VPSDZ	**0.99**	**0.99**	**1.00**	**1.00**												
VESTM	**0.99**	**0.99**	**1.00**	**1.00**	**1.00**											
VESTZ	**0.99**	**0.99**	**1.00**	**1.00**	**1.00**	**1.00**										
VESDM	**0.96**	**0.96**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**									
VESDZ	**0.96**	**0.96**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**	**1.00**								
OPSTM	**1.00**	**1.00**	**0.99**	**0.99**	**0.99**	**0.99**	**0.96**	**0.96**	**1.00**							
OPSTZ	**1.00**	**1.00**	**0.99**	**0.99**	**0.99**	**0.99**	**0.96**	**0.96**	**1.00**	**1.00**						
OPSDM	**0.99**	**0.99**	**1.00**	**1.00**	**1.00**	**1.00**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**					
OPSDZ	**0.99**	**0.99**	**1.00**	**1.00**	**1.00**	**1.00**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**	**1.00**				
OESTM	**0.99**	**0.99**	**1.00**	**1.00**	**1.00**	**1.00**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**	**1.00**	**1.00**			
OESTZ	**0.99**	**0.99**	**1.00**	**1.00**	**1.00**	**1.00**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**	**1.00**	**1.00**	**1.00**		
OESDM	**0.96**	**0.96**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**	**1.00**	**0.96**	**0.96**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**	
OESDZ	**0.96**	**0.96**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**	**1.00**	**0.96**	**0.96**	**0.99**	**0.99**	**0.99**	**0.99**	**1.00**	**1.00**

Source: VU Amsterdam elaboration

*all values different from 0 at 0.05 level

3.3 Research and policy implications

The composite indicator at business sector level developed in this section is helpful to gain better understanding of how the ML risk varies across different business sectors in the Netherlands. On the one hand, it **condenses a complex** and multifaceted phenomenon such as ML risk into a **single measure**. It can be used by policy makers, LEAs, supervisors and FIUs to identify the most vulnerable business sectors. This methodology can also supplement national risk assessments that have to be conducted to comply with the forty recommendations of the FATF (FATF, 2012).

The sector with the most ML risk is the **gambling and betting sector** (R 92). Other risky economic activities are, according to the IARM model, hotels, arts, security agencies, repair of computers and bars and restaurants.

Except gambling and betting, the most risky sectors stemming from the IARM analysis are generally not the ones that are at the moment specifically targeted with AML regulations (like financial institutions, real estate agencies, trust and company service providers, etc). But it must be noted that AML regulation is focused mainly on the ***placement phase* of the ML process**, while the risk factors considered by the IARM model seem to mainly focus on the ***integration* phase** (Reuter & Truman, 2004).

Even though the current AML regulation focuses primarily on the **gatekeepers** of the financial system, this analysis can be used as a basis to strengthen the policies for the riskier sectors in a broader sense. For instance, the **current administrative measure BIBOB** is restricted to a list of economic activities,[76] which could be extended/revised according to the IARM results. Indeed, some of the sectors that are generally selected for BIBOB procedures (hotels, bars and restaurants) also score high in our analysis, though this may be due the fact that the BIBOB measures are included as one of the proxy variables in our methodology.

A **sensitivity analysis** was carried out to verify whether the results of the analysis remain robust even after making different assumptions and statistical choices. The results appear solid with respect to a) the decision to use a PCA instead of simply adding up the identified proxies; b) the selection of risk factors and c) the choice of specific methodological parameters (e.g. related to the weighting, aggregation, rotation, etc.). All the alternative risk calculation methodologies tested give virtually the same results, and the correlation among all these alternative models is generally above 0.9.

76. This list is not uniform across the Netherlands, since each municipality can determine its own list. In this sense, the IARM approach could be useful for determining more systematically the list of economic activities to be monitored according for BIBOB.

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4. United Kingdom

The purpose of this chapter is to assess the risk of money laundering (ML) in the UK. This assessment, in line with FATF risk assessment guidelines, analyses ML threats and vulnerabilities at police area level in England and Wales. The assessment of ML risk in Scotland, Northern Ireland and at business sector level was not conducted due to paucity of data.

The chapter is structured as follows: first, it provides some background information on ML risk assessment and the AML landscape in the UK (Section 4.1). Second, it develops the ML risk indicator at sub-national area level across the 43 police territories of England and Wales (Section 4.2). Finally it presents problems encountered when trying to develop a business sector composite indicator for the UK (Section 4.3) and it discusses research and policy implications (Section 4.4).

Main findings - United Kingdom

- This pilot suggests that a methodology which uses a risk-based approach where money laundering (ML) threats and vulnerabilities are measured could be adopted in relation to 'area' or 'territory' level **ML risks in the UK**.
- The **paucity of data** in relation to UK threats and vulnerabilities remains a significant issue. This is particularly problematic when trying to identify threats at business sector level.
- The UK is at obvious risk of money laundering due to its position as a major world financial centre. Nationally, **a number of threats** can be measured – such as the number of organised crime groups operating and the volume of predicate offences.
- A number of **vulnerabilities** can also be identified – such as the cash intensiveness of much of the economy and the opaque shareholding and beneficial ownership structures of businesses.

Analysis at territory level: ML risk across the 43 police force territories of England & Wales[77]

- Threats and vulnerabilities measures are closely correlated – e.g. the presence of **organised crime**, the presence of shareholders and beneficial owners with connections to **risky jurisdictions** and **cash-intensive businesses**.
- The average distance to beneficial owners[78] of UK businesses is 1.5 – with businesses located in the **Channel Islands and Isle of Man** having the highest average at 3.7 and 3.4 respectively.
- London is the area that has the highest risk score for connections to shareholders from **'risky' jurisdictions**.
- Businesses in the mining, financial, energy and manufacturing sectors are most likely to have links to shareholders or beneficial owners from risky jurisdictions.
- Principal component analysis suggests that locations that are most exposed to serious and organised crime, where business have connections to risky jurisdictions and where there are cash intensive businesses may have **the highest risk of money laundering**.
- According to the threats and vulnerabilities data available, the **City of London** emerges as the area with the highest ML risk. Conurbations such as the **Metropolitan Police area, Greater Manchester** and the **West Midlands** also emerge as high risk areas.

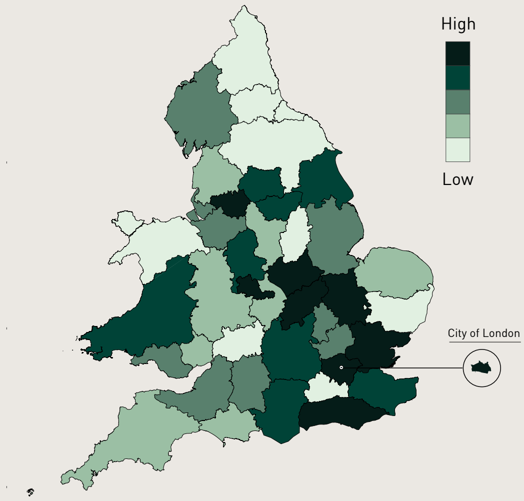
77. A full list of the 43 police forces of England and Wales is available on the POLICE.UK website: https://www.police.uk/forces/. Due to lack of workable data, it was not possible to extend the analysis to Scotland and Northern Ireland.

78. As described in chapters 2 (Italy) and 3 (the Netherlands), the beneficial ownership distance measures the average number of 'steps' which separate a company from its beneficial owner(s). The higher the BO distance, the more complex the ownership structure, the higher the ML risk.

Research and policy implications

- Although the approach outlined here is a pilot, it could be used to help support **future National Risk Assessments**.
- The risk-based framework could allow for a more **transparent methodology** to be developed to measure territorial and business level risks.
- Owing to the lack of threats data across business sectors it was not possible to develop **a risk-based model across business sectors** (as done in Italy and the Netherlands). A lack of threats data across geographical areas was also a limitation. This is a significant issue that needs to be addressed for future risk assessments.

ML risk across UK areas (all 43 police areas)



Source: University of Leicester elaboration

4.1 Introduction and background

Money laundering (ML) – and the criminal activity that creates the need to launder funds – represents a significant risk to the United Kingdom (HM Treasury, 2015). Money laundering is identified as a key enabler of serious and organised crime, the social and economic effects of which cost the UK an estimated **£24 billion per year** (Mills, Skodbo, & Blyth, 2013). Money laundered into or via the UK financial system is also linked to grand corruption (the bribery and theft of public funds) in other countries (Home Office/ HM Treasury, 2016).

The UK is widely recognised as facing a broad range of threats from money laundering, and it is considered particularly vulnerable due to its position as a world financial centre (Home Office/HM Treasury, 2016, p. 7):

- The UK is currently **the largest cross-border banking centre**;
- It accounts for 17% of the total global value of **international bank lending**;
- It accounts for 41% of global **foreign exchange** trading.

There are a number of key reasons why the UK, and its financial system in particular, is an attractive option for money launderers, which are summarised below in Table 39.

Table 39 – Factors making UK and attractive option for money laundering

Global financial hub	The high volume of **financial transactions** makes it easier to hide suspicious activity.
Offshore jurisdictions	The UK has unparalleled links with offshore jurisdictions, whose secrecy enables money to be hidden more easily. The key British offshore financial centres are the three Crown Dependencies (**Guernsey, Isle of Man and Jersey**); and, as a legacy of its colonial history, the UK has ties with 14 Overseas Territories, the most notable in terms of ML risk being: **Anguilla, Bermuda, British Virgin Islands, Cayman Islands, Gibraltar, Turks and Caicos Islands** (Foot, 2009).
Stability and security	The UK represents a **safe investment opportunity** for both legitimate and illegitimate/ corrupt businesses and individuals, with secure property rights and a stable political environment.
Professional competence	The UK has a vast network of **well-qualified professionals** who can facilitate transactions of any type.
Lifestyle	The UK enables individuals to merge easily into a global élite, **cleansing their reputations** and buying respectability for the next generation.
Property market	**High property prices** allow corrupt individuals to launder large sums of money within a single purchase, and there are currently loopholes in buyers' source of wealth checks.
Weaknesses in the UK anti-money laundering (AML) system	The UK has 27 supervisory bodies, resulting in an **AML system that is inconsistent, unclear and "structurally unsound"** (Goodrich & Cowdock, 2016, p. 6); and vulnerable to conflicts of interest for supervisory bodies that are both lobbying and promotional agents for their sector, as well as the AML enforcement authority.
Ineffective asset recovery*	The UK's confiscation system has been criticised for its low impact on **recovering criminal assets** (National Audit Office, 2013). Major changes are needed if the UK is to improve its capability to detect, freeze, seize and, where appropriate, accountably repatriate criminal assets that are invested in the UK from overseas.
* This issue has been recognised by the UK government, and the confiscation order system is currently undergoing a programme of reform – see Annex A4	

Source: University of Leicester elaboration of TI-UK Report, Paradise Lost (Goodrich & Cowdock, 2016, pp. 5–9)

The National Crime Agency (2015) asserts that money laundered in or via the UK includes the illicit proceeds of almost all serious and organised crime in the UK; plus the criminal proceeds of a substantial proportion of international serious and organised crime – including illicit funds and assets derived from corrupt Politically Exposed Persons (PEPs). However, in terms of scale, the true **extent and value of money laundering into and through the UK is not known**. Estimates vary considerably, but all indicate that the sums are substantial. For example, it has been reported that the amount of money laundered in or through the UK annually is likely to be at least £100 billion (Barrington,[79] cited in House of Commons Home Affairs Committee, 2016, p. 21); whereas, the National Crime Agency (2015, p. 21) assesses that hundreds of billions of US dollars of criminal proceeds are "almost certainly" laundered through UK banks and their subsidiaries, per annum.

Additionally, there is a clear overlap between **ML and terrorist financing** because similar methods are used by criminals and terrorist to move and store funds. As such, money laundering is recognised as a strategic threat to the UK's economy and reputation, and a significant threat to the UK's national security (HM Treasury, 2015; National Crime Agency, 2015a). The UK has a comprehensive AML regime in place, and it is committed to ensuring that the UK financial system is an increasingly hostile environment for ML (an overview of the UK anti-money laundering framework is presented at Annex A4) (HM Treasury, 2016b).

In order to try to understand the risk of money laundering, the first **UK National Risk Assessment (NRA)** of Money Laundering and Terrorist Financing was jointly produced by the UK Home Office and HM Treasury, and was published in October 2015. Below, some of the main findings and limitations of the NRA are outlined. In addition, the key policy implications which have been developed through the UK anti-money laundering action plan are outlined.

79. Robert Barrington, the Executive Director of Transparency International UK, reporting to the House of Commons Home Affairs Committee on the Proceed of Crime, Fifth Report of Session 2016-17 (http://www.publications.parliament.uk/pa/cm201617/cmselect/cmhaff/25/25.pdf).

The 2015 UK National Risk Assessment

The **FATF Recommendations** stipulate that "countries should identify, assess, and understand the money laundering and terrorist financing risks for the country" and that, based on this assessment, "countries should apply a risk-based approach (RBA)" to ensure that they implement AML/CTF measures that are commensurate with the identified risks (Recommendation 1 - FATF, 2012, p. 11 - see also Chapter 1).

The first **UK National Risk Assessment (NRA)** was based on extensive consultation with UK intelligence and law enforcement agencies, supervisors and private sector representatives. The NRA's aims and objectives are to identify, understand and assess the money laundering and terrorist financing risks faced by the UK; and to use this information to inform the appropriate allocation of resources to mitigate these risks (HM Treasury, 2015).

In developing the methodology for the UK NRA, the UK government considered risk assessment models developed and used by others, including the World Bank, IMF and other countries, along with the FATF guidance and feedback from key stakeholders from the UK's AML/CTF regime (HM Treasury, 2015). The UK NRA approach followed the three stages of assessment set out in the FATF Guidance – **identification, analysis, and evaluation** – with an analytical framework based on the key premise that risk is a function of three factors: threat, vulnerability and consequence (FATF, 2013a) and was based upon:

(i) **Consultation.** This first stage of the assessment identified vulnerabilities and threats through consultation with stakeholders from sectors subject to AML enforcement, law enforcement, supervisory authorities, government departments and NGOs.

(ii) **Data collection and analysis.** During the second assessment stage, data collected from stakeholders was analysed to identify the risks present, and to understand their impact.

(iii) **Risk rating.** This final stage of the UK NRA assessed each sector's relative exposure to risk using the NRA *risk rating model*, which is an adaptation of the UK National Crime Agency's draft Management of Risk in Law Enforcement model (**MoRiLE**). This adaptation decreased the reliance on quantitative data and allowed qualitative factors to be included in the assessment. The assessment of structural risk within each sector was based on a series of sector-specific vulnerability factors and the relative likelihood that the threat of money laundering will materialise in that particular sector.

The measure of vulnerability of each sector[80] was based upon:

- Business complexity (and international reach);
- Volume and speed of cash flow;
- AML compliance in sector.

The likelihood that a threat will materialise was based upon:

- Size of sector/ area;
- Likelihood of Suspicious activity reports (SARs) submission;
- Law enforcement knowledge of ML through the sector.

The NRA assumed the consequences of successful ML through any particular sector to be 'severe' (see HM Treasury, 2015, pp. 9–11).

The assessment of the above factors produced a risk score for each regulated sector, which was then categorised as Low, Medium or High risk, as detailed in the Table 40, below:

Table 40 – UK National Risk Assessment on Money Laundering: Risk Rating by Sector

Thematic area (sector)	Total vulnerabilities score	Total likelihood score	Structural risk	Structural risk level	Risk with mitigation grading	Overall risk level
Banks	34	6	211	High	158	**High**
Accountancy service providers	14	9	120	High	90	**High**
Legal service providers	17	7	112	High	84	**High**
Money service businesses	18	7	119	High	71	**Medium**
Trust or company service providers	11	6	64	Medium	64	**Medium**
Estate agents	11	7	77	Medium	58	**Medium**
High value dealers	10	6	56	Low	42	**Low**
Retail betting (unregulated gambling)	10	5	48	Low	36	**Low**
Casinos (regulated gambling)	10	3	32	Low	24	**Low**
Cash	21	7	147	High	88	**High**
New payment methods (e-money)	10	6	60	Medium	45	**Medium**
Digital currencies	5	3	15	Low	11	**Low**

Source: University of Leicester elaboration of (HM Treasury, 2015, p. 12)

80. Each sector within the regulated sector, which relates to individuals and firms that are subject to requirements under the UK Money Laundering Regulations 2007 (HM Treasury, 2015). See Annex A4.a for a list of the regulated sectors.

The key findings from the NRA are outlined in the box below.

Key findings of the UK NRA

In addition to identifying and producing an assessment of risk in the key sectors, or thematic areas, outlined above, the NRA presents a number of key findings:

- The UK's law enforcement agencies' intelligence appears to be **best in regard to cash-based laundering**, especially in relation to cash collection networks, international controllers and money service businesses, but acknowledge that there are some knowledge gaps.
- Because of its size and complexity, the **UK financial sector** is at more risk of ML than the financial sector in many other countries.
- Little is known about **'high-end' laundering**,[81] and risks at a local level.
- More research/intelligence is required in relation to the role of the financial and professional services sectors in ML – particularly professional enablers.
- Intelligence in relation to **high value dealers, gambling and new payment methods** is mixed.
- The effectiveness of the UK's supervisory regime is inconsistent, but improvement is required to a greater or lesser degree across all sectors.
- The report is also critical of the **UK's suspicious activity reports (SARs)** regime.

The publication of the UK NRA has been commended for its **clear and frank recognition of the high level of the UK's international and domestic ML risk** (Transparency International UK, 2015; Wood, 2015). However, it is of note that the NRA has not been particularly well-received by AML supervisors in the regulated sectors (Chartered Institute of Taxation, 2015; The Law Society, 2015), and several contentious areas have been identified relating to methodological issues, inconsistencies and limitations:

1. The level and spread of government engagement with the stakeholder groups during the consultation phase is uncertain. It is clearly stated in the NRA that the conclusions "draw heavily on expert judgement from law enforcement agencies, supervisory authorities and those responsible for AML/CFT within firms" (Home Office/HM Treasury, 2016, p. 10). However, nowhere is it made clear how many individuals were spoken to, in which specific organisations, and what they were asked.
2. In terms of the nature of the consultations, the NRA methodology states that "workshops were held with some sectors and questionnaires with others" (HM Treasury, 2015, p. 10). However, it does not state what was in the questionnaire or covered in the workshops.
3. There is a **lack of clarity** about how the risk ratings applied to the regulated sectors are calculated and applied (see Table 40 above).
4. There is **no geographical analysis** of the risks of money laundering.
5. The analysis of businesses covers regulated sectors. However, given that businesses in both regulated and non-regulated sectors[82] are potentially at risk of ML, the scope of future NRAs could be broadened to include sectors that are currently unregulated.

More details about some of the limitations of the NRA can be found at Section 4.3 of this report and also at Annex A4. However, notwithstanding the above concerns and issues, the NRA report has been viewed as a welcome acknowledgement that the UK must "raise its game" if it is to realise the government's promise that "there is no place for dirty money in Britain" (BBC News, 2015; Wood, 2015, p. 2). Indeed, it is stated in the report that the NRA will be used to shape the UK government's response to ML, and the NRA also sets out the priorities for the risk-based AML Action Plan that the UK government had committed itself to produce[83] (HM Treasury, 2015, p. 6). An overview of the action plan is set out at Annex A4.

The Action Plan is a demonstration of the UK government's commitment to tackling both money laundering and terrorist financing, and it represents the most significant reform of the UK's AML and CTF regime in over a decade (Home Office, 2016a).

81. 'High end' money laundering is particularly associated with major fraud and overseas corruption. It usually involves electronic transactions of substantial value (as opposed to cash). It also usually involves the abuse of the financial sector and the use of 'professional enablers' to facilitate the complex processes that are needed to ensure anonymity for the criminal (National Crime Agency, 2014a).

82. A list of regulated sectors, as set out in the UK Money Laundering Regulations (2007) is provided in Annex A4. A non-exhaustive list of individual sectors/entities examples is provided in Annex II of the FATF National Money Laundering and Terrorist Financing Risk Assessment Guidance (FATF, 2013a, pp. 46–49).

83. HM Government (2014) UK Anti-Corruption Plan, Action 43.

4.2 Analysis at sub-national area level

The approach presented in this section aims to build upon the UK NRA in several ways:

- It develops a methodological framework (based upon the approach to measuring threats and vulnerabilities as outlined by the FATF) for analysing the risk of money laundering;
- It identifies sources of data that can populate the methodological framework and operationalises them;
- It develops an analytical approach that allows identification of the most 'risky' territories (in this case police areas) for money laundering.

The approach is presented in **seven methodological steps** (see Chapter 1) which are also followed in the analysis in Italy and the Netherlands, and that outline:

1. How risk factors (threats and vulnerabilities) are identified;
2. How these risk factors are operationalised into proxy measures;
3. How the variables were normalised/the control measures that are used;
4. Initial analysis and exploration of the links between threats and vulnerabilities;
5. Identification of principal components that constitute ML risk across each territory;
6. Development of a ML risk composite indicator at area level;
7. Validation of the composite indicator

STEP 1 – ML RISK FACTORS IDENTIFICATION

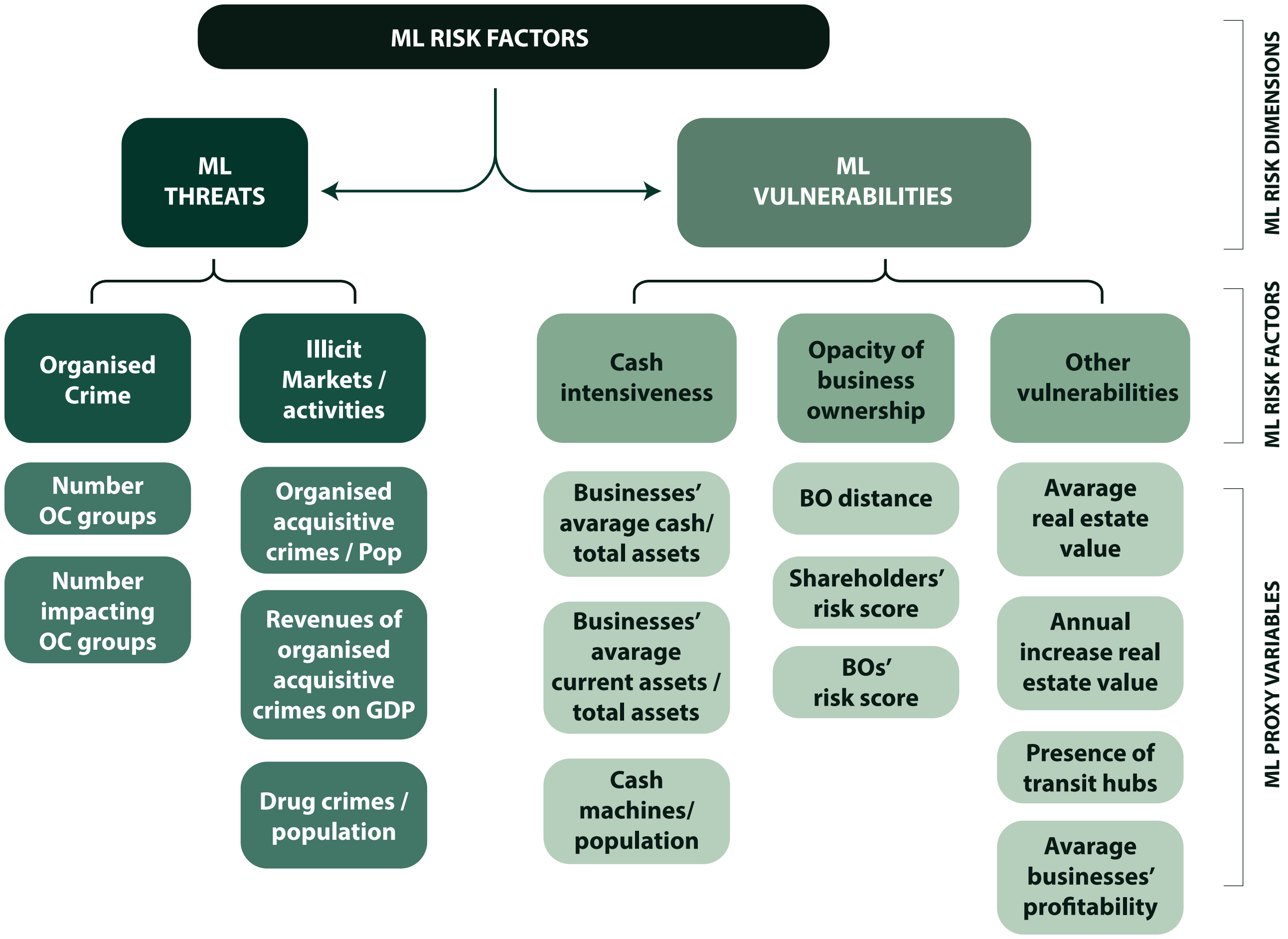
Identifying quantitative measures of national level risk factors (RFs) in relation to money laundering is obviously essential to any risk-based approach. This study has identified a number of threats and vulnerabilities from both academic and policy sources. These identified threats and vulnerabilities have (where possible) been operationalised in to sub-national level proxy measures.

The list of RFs suggested by FATF and relevant literature (see Chapter 1 and Annex) is very broad. However, the focus here is on RFs that:

- are **particularly relevant** in the UK context;
- allow for in-depth analysis because of **data availability.**

Identified RFs where some data were available are classified according to FATF taxonomy (*Threats, Vulnerabilities and Consequences* – see Chapter 1) and grouped into a tree-structure (risk dimensions, risk factors, etc.) which is depicted in the chart below. For the purpose of this analysis, the focus here is on **threats and vulnerabilities**. As with the analyses presented in the Italy and Netherlands (see Chapters 2 and 3), and in line with most NRAs conducted across EU countries, consequences are not covered by the model. Here, they are only discussed briefly but not included in the analysis.

Figure 42 - ML risk factors and proxy variables at sub-national area level



Source: University of Leicester elaboration

STEP 2 – ML RISK FACTORS OPERATIONALISATION

This section outlines how the identified threats and vulnerabilities, and in particular each risk factor, are (where possible) operationalised into one or more **proxy variables** in order to allow for their measurement and analysis. Proxies are identified according to previous literature and data availability, and are illustrated in the tables below (see Annex A4 for more details).

Money laundering threats

The sub-national threats variables that are developed fell into two main groups.

- First, the **number of organised crime groups** (OCGs) operating per area; and
- Second, the **money flows generated** from predicate offences across each area.

As said, most of identified variables apply only to England & Wales, while the availability of data as regards Scotland and Northern Ireland remains weak and does not allow in-depth analysis. An overview of the proxy measures of threats is presented in Table 41 below. In relation to the first, the hypothesis is that the higher the number of OCGs in an area, the more money that is generated through OC activity across a range of predicate offences, then the greater the amount of proceeds that one would expect to be laundered into the licit system. Indeed, the HM Treasury notes that serious and organised crime are seen as a key money laundering threat to the UK (See HM Treasury, 2016: AML and CTF Supervision Report 2014-15).

The list of **predicate offences** developed for this analysis is informed by the FATF (FATF, 2013a), as reported in the 4th AMLD (Directive 2015/849, Art. 3), those presented in the UK NRA (HM Treasury, 2015) and also from the predicate offences used by Mills et al (2013) in their estimate of the costs of organised crime.

Table 41 - ML threats: proxy variables at UK sub-national area level

ML Risk factor	ML Risk sub-dimension	Proxy variables	Description	Variable labels	Disaggre-gation level	Covered years
Organised crime (OC)	OC presence	Organised crime groups per 100,000 population	Number of organised crime groups operating in area	*OCG*	Police area	2016
		Organised crime impacting per 100,000 population	Number of organised crime impacting groups	*OCG_IMPACT*	Police area	2016
Illicit markets / activities	Organised acquisitive crimes	Grouped acquisitive crime per 100,000 population	Distraction burglary; metal theft; organised theft of motor vehicle; cash in transit robbery; plant theft.	*ACQUISITIVE*	Police area	2014-15
		Acquisitive crime revenues as % of GDP	Estimate of acquisitive crime revenues as % of local GDP.	*ACQUISITIVE _GDP*	Police area	2014-15
	Drug trafficking	Grouped drugs crimes per 100,000 population	Drugs trafficked and drugs seizures	*DRUG*	Police area	2012 - 2015
	Immigration crime	Grouped immigration crime per 100,000 population	Human trafficking, modern slavery and child sexual exploitation	*IMMIGRATION*	Police area	2013 - 2015

Source: University of Leicester elaboration of Mills et al., 2013.

Data in relation to the number of known OCGs in each area are provided by the National Crime Agency. Here estimates of the numbers of groups that are (a) located in each area or (b) are known to impact across each area are collected. Data protection protocol means that it is not possible to reveal the identity of areas with the highest numbers of organised crime groups, or where organised crime groups impact on the area. However, analysis reveals that, when considered as a rate per population the highest numbers of organised crime groups tend to concentrate in the **larger urban areas**.

The proxy measures of predicate crimes are developed by identifying (a) in what types of crime activities organised crime groups engage, and (b) what **proportion of these crimes** might be attributed to organised crime groups. Estimates of the proportion of crime thought to be committed by OCGs are largely based upon **Mills et al (2013)** estimates of the scale and the social/economic costs of organised crime. Mills et al. identify several crime types that are commonly committed by organised crime groups and then estimate the proportion of crimes across several categories that are directly related to organised crime. Column one of Table 42 presents these crime types with the estimate of the proportion that are linked to organised crime groups. The second column indicates if area-level data in relation to the predicate offences are available for analysis for the IARM study (the source of data is outlined at Annex A4).

Table 42 – Potential predicate offences as identified by Mills et al., 2013 and data available for UK area analysis

Predicate offences identified by Mills et al., 2013 (rate attributable to organised crime in brackets)	Data available for UK area analysis
Grouped acquisitive crimes, i.e.	
Distraction burglary – 100%;	Yes
Metal theft – 20%;	Yes
Theft of motor vehicle – 58%;	Yes
Cash and valuables in transit robbery – 100%;	Yes
Plant theft – 100%;	Yes
Fraud/forgery – 80%;	Yes
Road Freight crime – 100%;	No
Counterfeit currency – 100%;	No
Drugs supply/trafficking – 100%;	Yes[84]
Firearms supply – 100%;	No
Immigration crime (abuse of legitimate entry - 75%); human trafficking for sexual exploitation (100%); organised people smuggling (75%);	Yes: Human trafficking, kidnap, blackmail, modern slavery, child sexual exploitation.
Intellectual property crime and counterfeiting – 80%.	No

Source: University of Leicester elaboration of Mills et al., 2013

Although a number of predicate offences are identified, not all are included in the final analysis for several reasons. As outlined at Annex A4, **data on predicate offences are collected from a variety of sources**, and this raises issues concerning the quality and validity of data in many cases. The majority are collected from official recorded crime data sources, whereas others are collected from a number of agencies affiliated to police or government departments. Obviously, some care has to be taken in terms of interpreting these crime figures as they are based upon official statistics. While the problems with official crime statistics have been noted in previous literature (e.g. Maguire, 2012) it should be underlined that these statistics are based upon crimes that come to the attention of the police or other official bodies and may not be representative of the actual total extent of predicate offences across each area.

From the data available, it appears that the most valid proxy measures of predicate offences (and hence ML threats) is that represented by acquisitive and drug related crimes. Therefore, variables labelled '**grouped acquisitive crimes**' (including distraction burglary; metal theft; organised theft of motor vehicle; cash in transit robbery and plant theft) and '**grouped drugs crimes**' (including drugs trafficked and drugs seizures) are developed and used in the analysis (see Table 41).

In addition to using a measure of the numbers of crimes that occur in an area, where possible, a monetary value is also applied to give a proxy measure of the potential amount of money that might be laundered in relation to each crime type. This is problematic because **monetary estimates are only available for some acquisitive crime types and not for drug-related offences**. Here, estimates of the costs of crime are available in relation to average values of stolen property for the offences of distraction burglary, vehicle crime, metal theft, cash in vehicle transit robbery and plant theft.[85] The revenues generated by these crimes are developed into a variable that measured them as a percentage of GDP per each police area.

84. Fraud/ forgery are eventually omitted from the analysis due to problems in accessing area level data for a period of at least 12 months. Some area level data are available http://www.actionfraud.police.uk/fraud-statistics though not for all areas.

85. The average costs applied to these crime types was £2,040 for distraction burglary (Mills, Skodbo, & Blyth, 2013, p. 56); £2,500 for vehicle crime (Mills et al., 2013, p. 60); £2000 for metal theft (Home Office, 2013); £15,000 for CIVT (SaferCash –data supplied), and £17,000 for plant theft (Paniu –data supplied).

Other potential indicators of threats are considered - such as **tax gaps data** and **asset confiscation**. The UK tax gap for 2014-15 is estimated to be £36 billion, which equates to 6.5% of tax that should, in theory, have been collected by HMRC for that year (theoretical tax liabilities). This is a reduction from 6.9% of theoretical tax liabilities for the previous year 2013/14. Over the longer term, there has been a downward trend in the tax gap, from 8.3% of theoretical tax liabilities in 2005/06 to 6.5% in 2014/15 (HMRC, 2016) see Annex A4 for further details). Unfortunately, **tax gap data are not available at a sub-national level** in the UK or by business sectors, and therefore could not be included in the analysis.

Confiscated assets could also be an alternative measure of organised crime infiltration (see Chapter 2 on Italy). **Asset confiscation** is the main means by which the government seeks to deprive criminals of their illicit gains (National Audit Office, 2013). In 2014/15, 5,924 confiscation orders were issued, and 1,203 restraint orders were used to freeze offenders' assets. In terms of monetary values for 2014/15, £155 million was collected by enforcement agencies from confiscation orders. However, the total debt outstanding from confiscation orders (as at September 2015) was £1.61 billion, of which only around £203 million was estimated by HM Courts and Tribunals Service to be realistically collectable (National Audit Office, 2016).

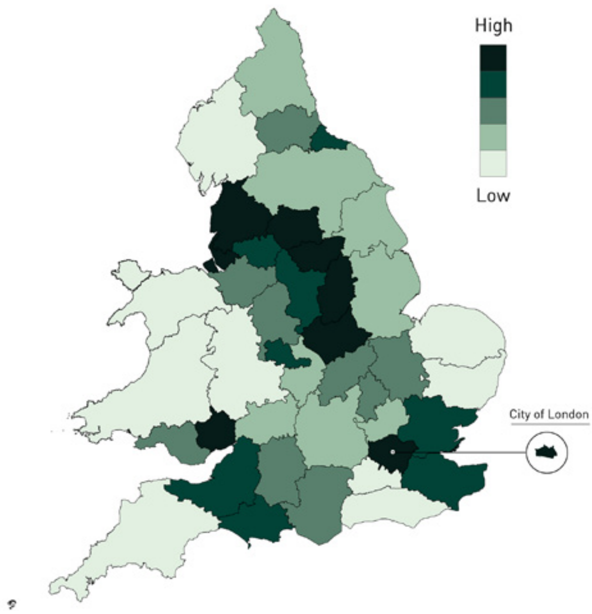
The confiscation orders system has been criticised by the National Audit Office and the Committee of Public Accounts for being ineffectively implemented and poor value for money, and it is currently in a process of reform (Home Office, 2017; National Audit Office, 2016 - see Annex A4 for further details). As a potential threat variable at geographical or business level, it is also identified that confiscation orders are limited because it is **difficult to obtain data disaggregated to area or business sector level**. Therefore, this measure could not be included in the sub-national analysis.

Overview of threat variables at UK sub-national level

Below, a descriptive spatial analysis for the threats variables is presented.

Figure 43 presents the rate (per 100,000 population, per year) of grouped acquisitive organised crimes per area. The average number per area is 188 crimes per 100,000 inhabitants per year. Overall, the highest rate is 1,721 as observed for the City of London, 248 for Leicestershire and 224 for Nottinghamshire.

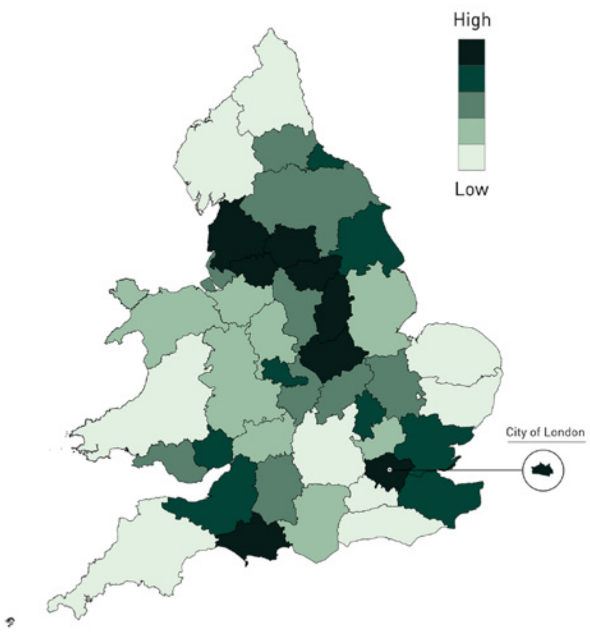
Figure 43 – Organised acquisitive crime per 100,000 population per area



Source: University of Leicester elaboration of Home Office data

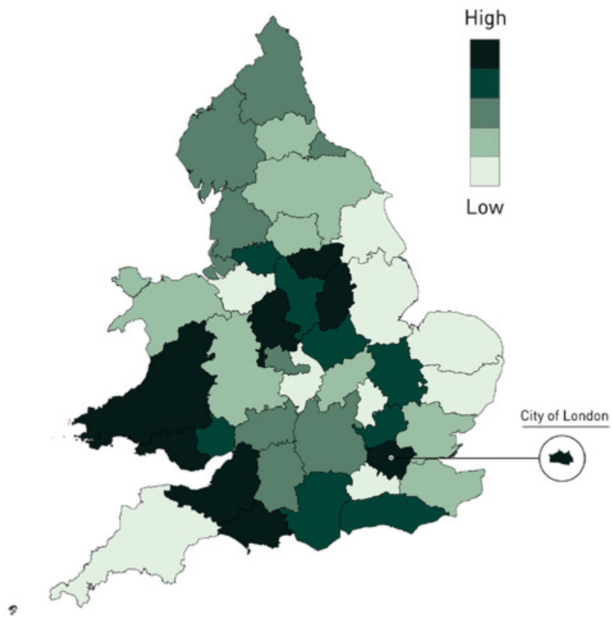
Figure 44, provides a geographical illustration of 'organised' acquisitive crime revenues as a proportion of local GDP. This shows that as a % of GDP the areas that generate the highest potential proceeds from organised acquisitive crime are the City of London, Leicestershire, the Metropolitan Police area and South Yorkshire.

Figure 44 – Organised acquisitive crime revenues per % of GDP per area



Source: University of Leicester elaboration of Home Office data

Figure 45 – Organised drug crimes per 100,000 population per area.



Source: University of Leicester elaboration of Home Office data

Finally, Figure 45 presents the average rate of drug trafficking and seizures per area. The national average is 561 crimes per 100,000 population, with the highest rates observed for the City of London, followed by Avon and then Dyfed-Powys.

A final threat variable that is constructed related to organised immigration crime. Here there tends to be a concentration within large urban areas. The average per area is 31 per 100,000, with the highest rates in the Metropolitan police area (322 per 100,000), Greater Manchester (143 per 100,000) and West Yorkshire (117 per 100,000).

Money laundering vulnerabilities

A number of vulnerabilities variables are identified in the previous literature, although (as with the threats variables) problems are encountered in terms of accessing appropriate measures that could then be operationalized for analysis at area level (see Chapter 1 and Annex). A list of variables that are used in the analysis and brief description of each is presented in Table 43.

The vulnerabilities proxy measures fell into three broad groups – those related to **cash-intensiveness, opacity of business ownership**, and further variables that are grouped as '**other vulnerabilities**' (such as real estate costs/values, presence of international transit hubs, and measures of business profitability). A full description of the variables is presented at Annex A4 and the sources of data are outlined. The majority of data in relation to vulnerabilities are collected from **Bureau van Dijk (BvD)**. BvD data are based upon a sample of 3,741,300 businesses in the UK. It is recognized that this number is lower than the total UK business population, which is over 5 million.[86] A comparison of the coverage of BvD to the whole UK business population (by business sector) is presented at Annex A4.

86. The lower number depends on the fact that BvD databases do not include all types of businesses and legal forms. For example, individual enterprises and unlimited companies are not fully covered, while limited companies are comprehensively mapped.

Table 43 – ML vulnerabilities in the UK

ML Risk factor	ML Risk sub-dimension	Proxy variable / description		Variable labels
Cash intensiveness	Presence of cash intensive businesses	Business cash intensiveness measure 1	Average ratio Cash / Total assets	*CASH_ASSETS*
		Business cash intensiveness measure 2	Average ratio Current assets / Total assets	*CURRENT_ ASSETS*
	Availability of cash in local area	Presence of cash machines per 1m population		*ATM_POP*
Opacity of business ownership	Complexity business ownership structure	% non-UK beneficial owners in UK business		*FOREIGN_BO*
		% non-UK shareholders in UK business		*FOREIGN_SH*
		BO distance		*BO_DISTANCE*
	Ownership links with risky jurisdictions	BOs' risk score		*RISKY_BO_w*
		Shareholders' risk score		*RISKY_SH_w*
Other vulnerabilities	Attractiveness of local area for investment	Average real estate value		*RE_COST*
		Annual increase in real estate values		*RE_CHANGE*
	Presence of transit hubs	Number of transit hubs such as ports and international airports		*TRANSIT_HUB*
	Profitability	Average business profitability		*PROFITABILITY*
ML Measures and control variables	Money Laundering Offences	Proceeds of Crime Act 'money laundering' offences per 1m population (2012 – 2015)[87]		*POCA*
	Regulated Businesses	% of businesses subject to ML regulations		*REGULATED*

*Variables ending with "_w" are weighted for the average company size in the area so as to control for the presence of multinational companies

Source: University of Leicester elaboration

An overview of descriptive statistics in relation to the vulnerabilities variables is presented below.

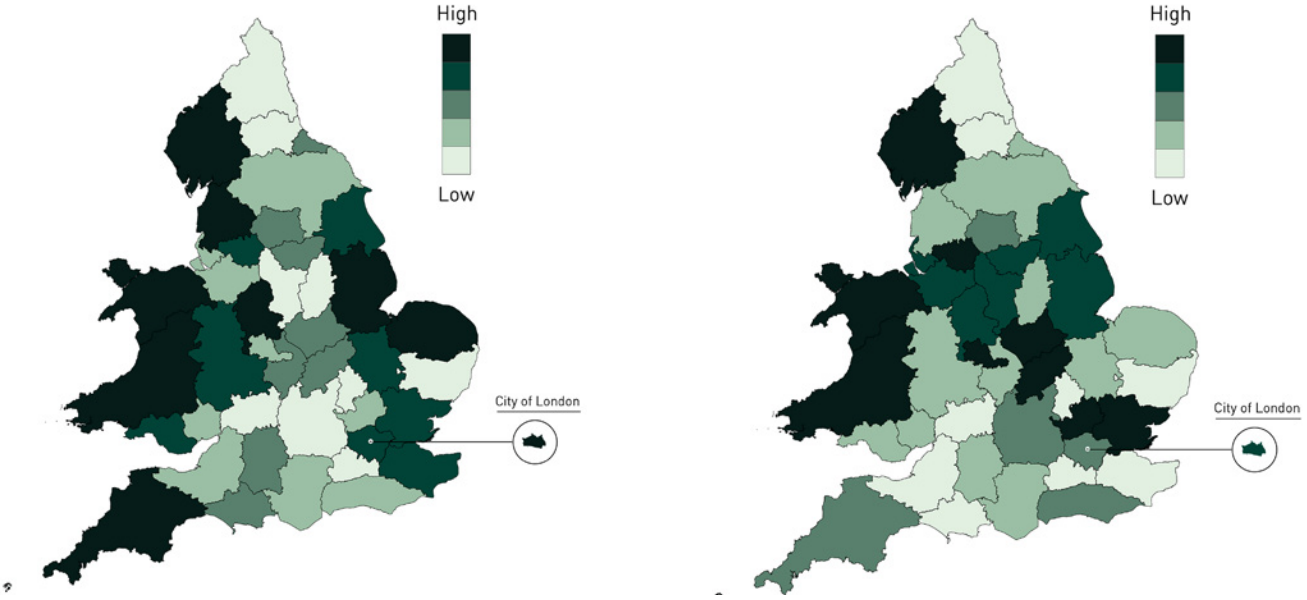
Cash-intensiveness of businesses

As highlighted elsewhere in this report, 'cash-intensiveness' has been identified as a facilitator of crime and money laundering. While in Italy data on cash diffusion among individuals by area level are available (see Chapter 2), in the UK they are unfortunately lacking. Therefore, in order to measure the degree of cash-intensiveness across regions, the presence of **'cash rich' or cash-intensive business** is measured. This is done in two ways (see Table 43).

The first measure represents the average ratio, per area, between local businesses' cash and cash equivalent on their total assets; the second, the average ratio of current assets on total assets (see Chapters 2 and 3 for details). Using the first measure, the most cash intensive businesses are located in the City of London, followed by Dyfed Powys and Staffordshire. Using the second measure, Northamptonshire, the West Midlands and Greater Manchester emerge as the areas with the most cash intensive businesses. Below a map is presented which compares these two measures (Figure 46).

87. A full overview of how money laundering offences are recorded in the UK is presented in Annex A4.

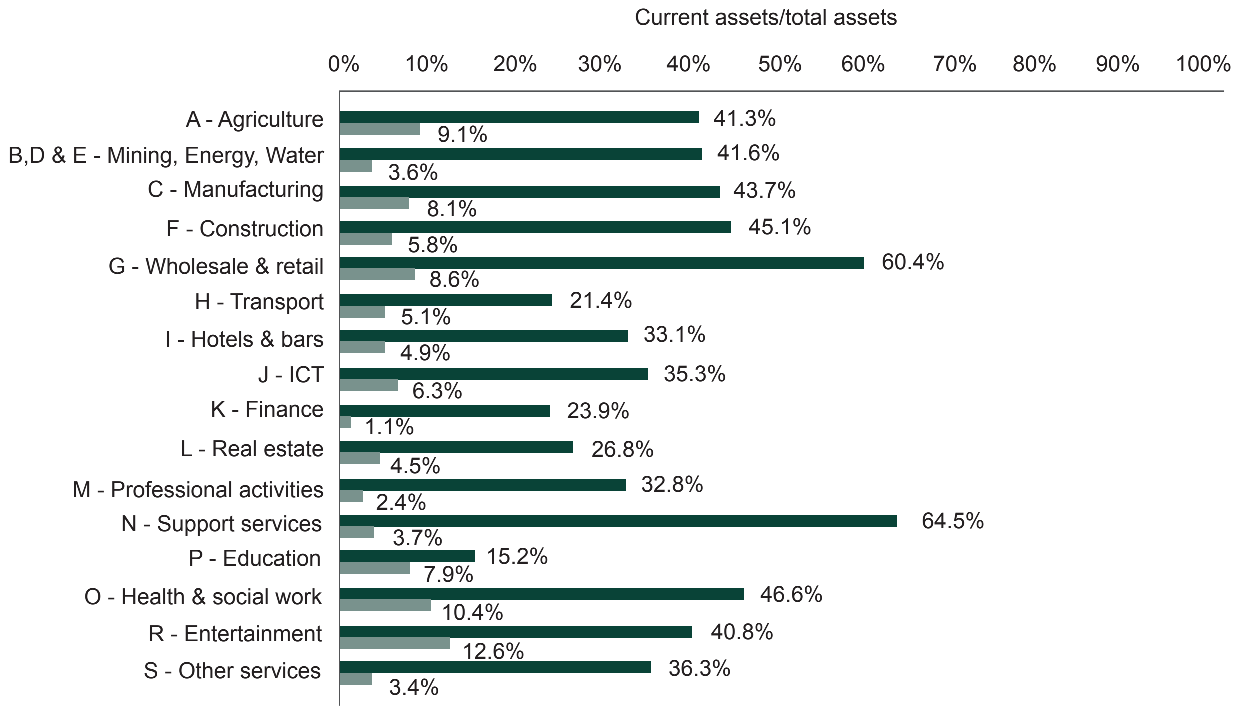
Figure 46 – Cash-intensive businesses across UK areas
Area average Cash / total assets ratio (left) and Current assets / total assets ratio (right). Last available year



Source: University of Leicester elaboration of BvD data

Below, these measures of cash intensity are considered across business sectors (Figure 47). This shows a high degree of liquidity (using the first method, i.e. the weight of cash and cash equivalents) in sectors such as **entertainment** (Section R - which includes regulated business types such as gambling, betting agencies, videolottery), social work, agriculture and wholesale/retail. When using method 2 (current assets) administrative support services, wholesale/retail trade and construction are the most 'liquid' sectors.

Figure 47 – Cash-intensive businesses across business sectors in the UK
NACE 2007 sections - excluding O, T and U. Last available year



Source: University of Leicester elaboration of BvD data

There are other indicators of territorial level risks in relation to 'cash intensiveness' or 'ease of payments' that are highlighted in the literature and for which some UK data are available. For example, sometimes the cash intensiveness of an economy can be measured by **the number of cash machines (ATM) within a geographical area.** Some geographical data are available on the use of cash machines across England and Wales (see UK Payment Statistics - Payments UK, 2015). On average there are 1,003 cash machines per 1m population per police area. Although the highest numbers are in Lancashire (1,617 per 1m population in Lancashire), the highest ratios tend to be in large urban areas such as Greater Manchester (1,261 per 1m population) and West Midlands (1,240 per 1m population).

Opacity of business ownership

Of course, business ownership structures where **beneficial ownership is difficult to identify** or where shareholding is complex have been identified as being a key vulnerability for money laundering (ECOLEF, 2013; FATF, 2016b). Within the UK context, identifying these structures is made difficult by the paucity of available data. Here the analysis relies on BvD data, which in itself provides limited coverage (see Annex A4). However, in Table 44 below, an overview is presented of: shareholding in companies, average distance to beneficial owners, and risk measures in relation to both shareholders and beneficial owners.

Table 44 – Data on ownership of businesses, by nationality, shareholder and BO (by territory)[88]

	UK	Foreign	Nationality not available	TOTAL UK
N. Companies	-	-	-	3,741,330
N. Shareholders (known = 1,084,470)	1,011,248	73,222	5,689,310	6,773,780
N. Beneficial Owners (known = 262,398)	162,884	99,514	7,981,085	8,243,483
Ratio shareholders to companies	-	-	-	1.8
Ratio beneficial owners to companies	-	-	-	2.2
Ratio shareholders to beneficial owners	6.2	0.74	0.71	0.8
Average BO distance[89]	-	-	-	1.6[90]

Source: University of Leicester elaboration of BvD data

Level of complexity of UK businesses' ownership structure

Table 44 indicates that, on average, the 3.7m UK companies listed by BvD have an average of 1.8 shareholders and 2.2 BOs, which suggests that for most companies there is direct ownership control (although these numbers are higher than in the other countries analysed by IARM – see Chapter 5). However, this does vary by region and business type.

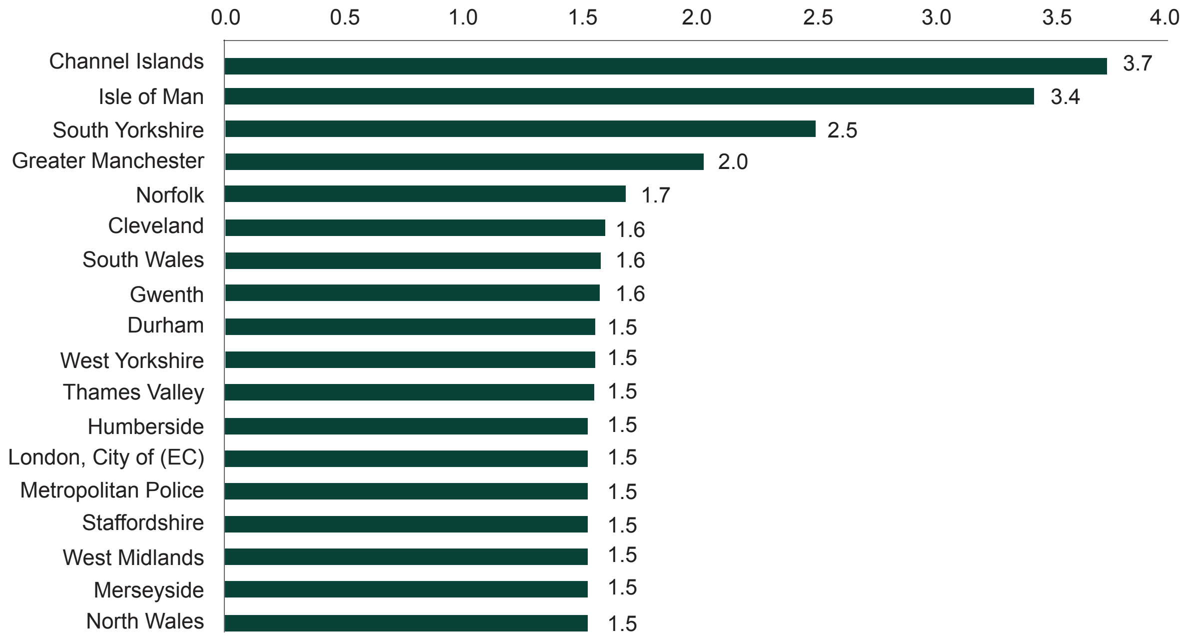
For example, Figure 48 presents all of the locations in England and Wales where the distance to beneficial owner is over the average of 1.5. Of the 16 areas above the average, seven are metropolitan areas. However, it is worth noting that two areas not included in the English and Welsh police area analysis – the **Channel Islands and the Isle of Man** – are the highest scoring areas overall, the average distance to the beneficial owner being 3.7 and 3.4 respectively (based on a sample size respectively of 5,416 and 3,170 beneficial owners across each area).

88. The data presented here use territory as the baseline. If businesses are used as the baseline, the figures alter. For example, there are 883,035 UK shareholders and 87,790 foreign shareholders who can be attributed to business types. There are 145,002 UK beneficial owners and 81,133 foreign beneficial owners who can be attributed to business types.

89. As described earlier (see Chapter 2 and 3), the beneficial ownership distance measures the average number of 'steps' which separate a company from its beneficial owner(s). The higher the BO distance, the more complex the ownership structure, and the higher the ML risk. If BO distance equals 1, then a company is directly controlled by its BO(s).

90. 1.5 excluding Channel Islands (3.7) and Isle of Man (3.4)

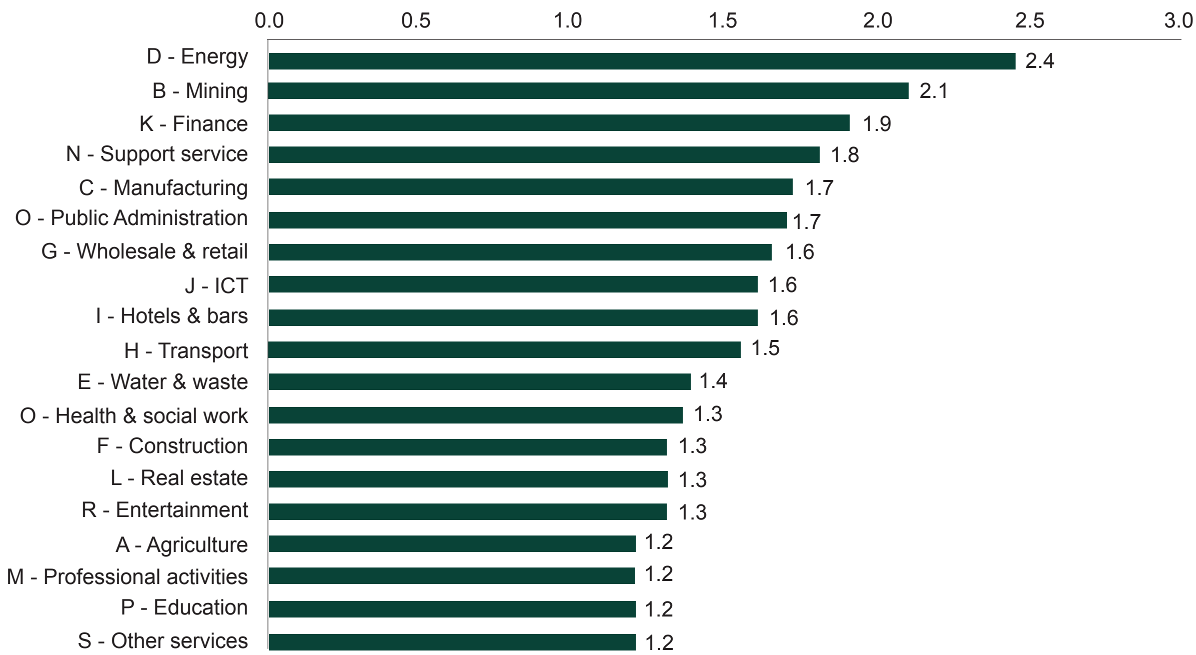
Figure 48 – Average BO distance at sub-national area level
UK areas with average BO distance above 1.5. Last available year



Source: University of Leicester elaboration of BvD data

Figure 49 illustrates the average distance to beneficial owner(s) by business sector. While the UK average is 1.5, a number of sectors recorded scores above this: for example, the **energy sector (2.4), mining sector (2.1) and financial sector (1.9**). The lowest average is in the legal sector at 1.2. It can be clearly seen – as also observed in Italy and the Netherlands (see Chapters 2 and 3) – that the economic activities characterised by higher BO distance are those with the highest number of **multinational companies** and highest volume of FDI.

Figure 49 – Average BO distance per business sector (ranked high to low)
NACE 2007 Sections excluding O, T, U. Last available year



Source: University of Leicester elaboration of BvD data

Business ownership connections with risky jurisdictions

While distance to beneficial owner is a useful vulnerability measure, the **connections that specific geographical areas or business types have to 'risky jurisdictions' through beneficial owners or shareholders** can be better understood by considering the level of 'risk' of the national jurisdiction of BOs or shareholders.

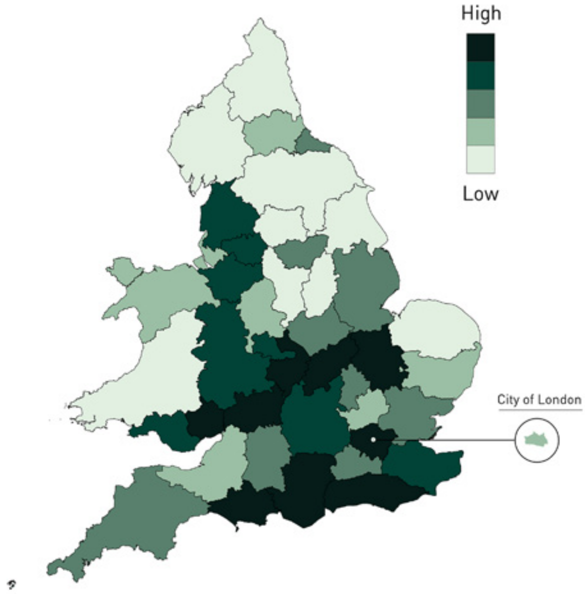
The degree of connections with risky jurisdictions is calculated by multiplying the **relevant Secrecy Score of the Financial Secrecy Index** (FSI)[91] for the weight of each nationality of BOs and shareholders by UK area (see Chapter 2, 3 and Annex for details). As explained earlier (see Annex) the values are weighted by average company size[92] in order to control for the presence of multinational companies and in order to identify the actual anomalies in business ownership structure. As illustrated in Figure 50, the highest average shareholder risk scores are London, Sussex and Cambridgeshire – each of these areas had scores that are around twice the average, suggesting more connections with risky jurisdictions.

For beneficial owners (see Figure 51 below), the highest ranking risk areas are Sussex, North Yorkshire and Merseyside – with all of these scoring around double the average. It is interesting to note that some locations – such as Sussex, London, Gwent, Northamptonshire and Gloucestershire – score relatively highly in relation to both BOs' and shareholders' risk.

91. The Secrecy Score is a component of the Financial Secrecy Index (FSI) developed by the Tax Justice Network and issued every 2 years. The secrecy score is a composite indicator which evaluates different dimensions of secrecy in the financial sector and in the legislation of selected jurisdictions. In particular, it evaluates: A) the level of banking secrecy; B) access to beneficial ownership information; C) corporate transparency; D) efficiency of tax and financial regulation; E) compliance with international standards; F) international cooperation (Tax Justice Network, 2015). For further detailed see Annex. The secrecy score has been preferred to other measures of risky jurisdictions (e.g. international or national blacklists) because of its independency and transparency of the evaluation methodology.

Figure 50 – Connections to risky jurisdictions: Shareholders' risk scores

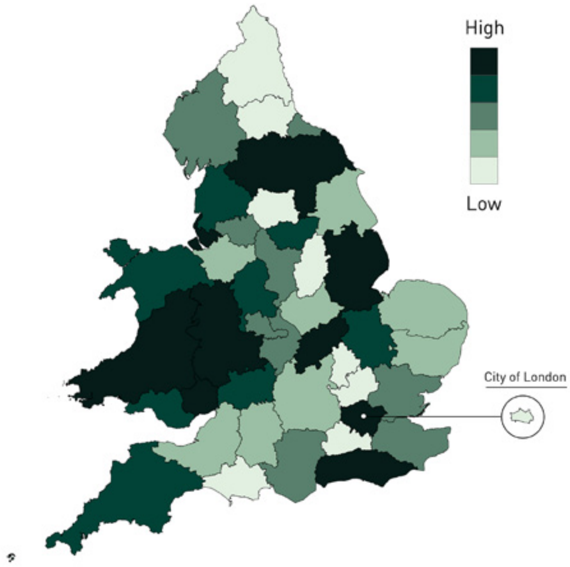
Weighted by average company size



Source: University of Leicester elaboration of BvD and TJN data

Figure 51 – Connections to risky jurisdictions: BOs' risk scores

Weighted for average company size



Source: University of Leicester elaboration of BvD and TJN data

92. As a measure of company size, the average ratio per area of employees/companies was computed. Other methods to weight the data are considered – such as by 'assets/companies' or 'turnover/ companies'. It has been decided to use 'employees/companies' because BvD data in relation to the distribution of employees across companies and territories are more robust in the UK than those for assets or turnover.

The same method is used to consider **connections to risky jurisdictions by business sector**. The table below presents the rank order by business sector for the respective risk scores for shareholders and beneficial owners, both weighted and unweighted by average company size. The most risky connections in relation to shareholders are in the **mining, financial and energy sectors** – which, as said, are also characterised by a higher number of multinational companies. These sectors also rank high in relation to beneficial owners (Pearson correlation of .544).

However, when weighted by the average company size, the most risky connections in relation to shareholders are in sector **A (Agriculture), G (Wholesale and retail trade) and R (Entertainment)**, while the most risky connections in relation to beneficial owners are section I (Accommodation), G (Wholesale and retail trade) and L (Real estate). The score of **real estate activities** remains unchanged after the weighting. As before, the rank order shows similarities for both categories (Pearson correlation of .603).

Table 45 – Connections with risky jurisdictions by business sector: Shareholders and BOs' risk score ranks

Unweighted and weighted by the average company size

NACE Section	Rank			
	Shareholders' risk - unweighted	**BOs' risk - unweighted**	**Shareholders' risk - weighted**	**BOs' risk - weighted**
B - Mining	1	2	15	17
K - Finance	2	5	19	19
D - Energy	3	1	17	12
C - Manufacturing	4	4	7	6
E - Water & waste	5	12	14	16
N - Support services	6	7	12	11
J - ICT	7	6	5	4
H - Transport	8	10	8	9
M - Professional activities	9	8	16	13
G - Wholesale & retail	10	9	2	2
L - Real estate	11	3	10	3
R - Entertainment	12	15	3	7
S - Other services	13	13	9	10
I - Hotels & bars	14	11	6	1
F - Construction	15	14	11	14
A - Agriculture	16	17	1	8
Q - Health & social work	17	16	4	5
P - Education	18	18	13	15
O - Public sector	19	19	18	18

Source: University of Leicester elaboration of BvD and TJN data

While connections to ‘risky jurisdictions’ have been identified as a money laundering vulnerability, the point needs to be made that, within the UK, the BvD data indicate that the shareholders and beneficial owners from the highest risk jurisdictions only form **a small proportion of the overall shareholder or beneficial owner population**. Indeed, BvD data indicate that at territory level and where nationality is known, around **9% of shareholders and 38% of beneficial owners in the UK are foreign**. Overall, BvD data identify over 150 different nationalities of shareholders and 75 different nationalities of beneficial owners of UK businesses.

However, the highest proportion of foreign shareholders and beneficial owners are from countries that do not score highly in relation to the FSS, such as the **USA, Germany and the Netherlands**. Table 46 outlines the percentage that each of the top ten listed nationalities contributes to the overall foreign shareholding and beneficial ownership across UK companies. The figures in brackets relate to (a) the FSS rank of the nationality (out of 173 nations covered by FSS) and (b) the actual FSS score.

It can also be observed that the highest ‘risk’ nationality (according to the FSS) in the top ten list of UK shareholders or beneficial owners is **Switzerland**, which ranks at 33 out of the 173 nations with an FSS score. If one considers the nations with the highest FSS, these tend to make up a very low proportion of shareholders or beneficial owners in the UK. For example, shareholders and beneficial owners from the top ten FSS scoring nationals make up less than 1% of UK shareholders and 1% of beneficial owners.

Table 46 – Shareholders and beneficial owners nationality in the UK First ten nationalities. % of all non-UK
In brackets: FSS rank/FSS score

Shareholders		Beneficial Owners	
Country	**% (FSS rank/score)**	**Country**	**% (FSS rank/ score)**
United States	24.3% (61/60)	Spain	28.7% (99/33)
Germany	8.8% (63/56)	Italy	21.4% (97/35)
the Netherlands	6.4% (75/48)	Germany	12.5% (63/56)
Ireland	5.6% (88/40)	United States	6.0% (61/60)
France	5.3% (84/43)	Switzerland	4.0% (33/72)
Switzerland	4.1% (33/72)	Saud Arabia	3.5% (59/61)
Australia	3.2% (83/43)	South Africa	2.4% (85/42)
Italy	3.2% (97/35)	Ireland	2.1% (88/40)
Luxemburg	3.0% (64/55)	the Netherlands	2.0% (75/48)
Sweden	2.1% (94/36)	France	1.8% (84/43)

Source: University of Leicester elaboration of BvD data

93. As indicated previously, this depends on what baseline measure is used. If the proportion is calculated based on the cases where the nationality of the SH or BO is known for business sectors, then the calculation is (for SH) 87,790/970,825 = 9% and (for BO) 81,133/226,135=36%

It should, however, be borne in mind that from 6 April 2016, it became a legal requirement in the UK that all companies keep a register of '**people with significant control' (PSC) – or 'beneficial owners**' – of the company, and that all companies will be required to file this information with Companies House[94] annually in a 'confirmation statement' from 30 June 2016 (Lloyd, 2016). A PSC is a person in the company who (Companies House, 2016):

- owns more than 25% of the company's shares;
- holds more than 25% of the company's voting rights;
- holds the right to appoint or remove the majority of directors;
- has the right to exercise, or actually exercises, significant influence or control;
- holds the right to exercise, or actually exercises, significant control over a trust or company that meets any of the other 4 conditions.

Companies will be required to provide detailed information about PSCs relating to (Companies House, 2016):

- the date that the individual became a registrable person;
- their name, country/state of residence and nationality;
- their service address;
- their usual residential address (this is not shown on the public register);
- their full date of birth (this is not shown on the public register);
- the nature of their control over the company.

It will take up to a year before PSC records at Companies House are complete because company filing dates for the confirmation statement are based on the anniversary of individual companies' incorporation (Lloyd, 2016). Nevertheless, the PSC data that will be held by Companies House harbours the potential to be a valuable source of information regarding beneficial owners from high risk jurisdictions for future ML risk assessments.

Other measures of vulnerabilities

Other vulnerability measures are also developed around real estate values, international connections/ transit hubs and business profitability.

Real estate values have often been considered a money laundering risk factor (see, for example, Ferwerda & Unger, 2013), especially in the UK, where the property market has been highlighted by numerous sources as a potential factor of attractiveness for illicit inflows. Therefore, consideration is given for identifying areas that might be most attractive for inward investment by using real estate value as a proxy measure of the sector attractiveness. This is primarily done by considering average real estate values and increases in real estate values per year from UK BEIS data. In relation to the average cost of real estate, the mean value in 2015 was £250,000, with the highest (£537,000) in the City of London and the Metropolitan area and the lowest (£157,000) in the North East.[95] The disparities in average real estate costs are also reflected in average real estate price increases per year (Pearson's r =.825). In London these are on average 13% growth as compared to less than 5% in the North East and North West of England.

94. Companies House is an executive agency sponsored by the UK Government Department for Business, Energy and Industrial Strategy. Companies House is responsible for incorporating and dissolving limited companies, registering the information that companies are legally required to supply, and making that information available to the public (Gov.UK, 2016).

95. Based upon UK Office for National statistics House Price Index Data: see https://www.gov.uk/government/statistical-data-sets/uk-house-price-index-data-downloads-november-2016

International connections/transit hubs are identified as a potential vulnerability to money laundering. Indeed, areas that have an abundance of international connections – via for example, transit hubs – are often characterized by higher volumes of illicit flows of cash (e.g. cash-smuggling – see Chapter 1). A measure of these connections is created by giving each police area a risk rating based upon the presence of international transit hubs – such as international airports, international railway stations, passenger ferry terminals and cargo ports. This shows that areas that can be described as possibly vulnerable due to the presence of transit hubs include port areas, such as Humberside, and areas with major international airports, such as London.

Finally, some data are available from BvD in relation to **business gross profitability**: namely the EBITDA/Turnover ratio. There is a (debated) hypothesis that profitable businesses may act as an attractor of inward investments for criminal groups and are thus a good indicator of where money laundering may occur. In the UK, it is revealed that the business sectors with highest gross profitability are:

- Real estate (20% EBITDA margin);
- ICT (15%);
- Mining, energy and water (14%);
- Professional services (12%).

However, questions have been asked about the correlation between business profitability and money laundering (see Riccardi, 2014). Therefore this proxy measure is omitted from the principal component analysis presented in step 5 below.

Alternative measures of money laundering

The data presented above are all indirect measures of ML threats or vulnerabilities. Attempts are also made to collect data in relation to a number of more direct measures of money laundering risk – such as **suspicious activity reports** (SARs) data and **proceeds of crime** data.

The volume of SARs submitted to the UK Financial Intelligence Unit (UK FIU) each year is substantial and continues to rise annually. For example, for the year 2014/15, the total number of SARs received is 381,882, an increase of 7.82% on the previous year (2013/14) (National Crime Agency, 2015b). Further information about the volume of SARs submitted in total and by sector is provided in the box below.

In recent years, however, increasing concerns have been raised about the **effectiveness of the SARs regime** – particularly in terms of the volume of SARs being submitted, and the capabilities of the SARs database (the ELMER IT system) to conduct useful analysis of SARs. Therefore this variable is limited as a potential measure of money laundering for two reasons. First, at present, no geographical analysis of SARs has been completed or could be completed using the current ELMER system. Second, because the overwhelming majority of SARs are made via the banking sector as part of their compliance with ML regulations, it tells us little about the distribution of threats across business sectors.

Suspicious Activity Reports (SARs) in the United Kingdom

A Suspicious Activity Report alerts law enforcement that a particular client – or their activity – is suspicious in some way that may indicate money laundering or terrorist financing. Table 47 below shows the steady increase in the volume of SARs submitted between October 2012 and September 2015:

Table 47 - SARs submitted to the UKFIU

Key statistics	Oct 2012 to Sept 2013	Oct 2013 to Sept 2014	Oct 2014 to Sept 2015
Total SARs	316,527	354,186	381,882
Consent SARs	14,103	14,155	14,672
Consent SARs refused (and %)	1,387 (9.8%)	1,632 (11.5%)	1,374 (9.4%)
Breaches of confidentiality	2	2	3

Source: University of Leicester elaboration of National Crime Agency (2013, 2014, 2015)

The NCA SARs annual reports (National Crime Agency, 2014b, 2015b) also present SARs submission breakdowns by sector. A summary for the year 2014-2015 is provided below in Table 48, which shows that the vast majority of SARs are submitted by the banking sector. Information relating to the value of seizures, restrains and arrest figures arising from consent SARS is provided at Annex A4.

Table 48 - SARs submission by sector 2014/2015

Oct 2014 to Sept 2015	Volumes	% of total	% comparison to 2013-2014
Credit institution – Banks	318,445	83.39%	+9.41%
Credit institution – Building societies	15,806	4.14%	+23.16%
Credit institution – Others	11,828	3.10%	+17.18%
Financial institution – Money service businesses	11,120	2.91%	-25.82%
Financial institution – Others	6,835	1.79%	-0.48%
Accountants and tax advisers	4,618	1.21%	-6.33%
Independent legal professionals	3,827	1.00%	+6.01%
Trust or company service providers	101	0.03%	-42.94%
Estate agents	355	0.09%	+98.32%
High value dealers	135	0.04%	-59.21%
Gaming (including casinos) / Leisure (including some not under ML Regulations)	1,431	0.37%	+52.40%
Not under ML Regulations	7,381	1.93%	-9.76%
Total	**381,882**	**100%**	**+7.82%**

Source: University of Leicester elaboration of (National Crime Agency, 2015b, p. 10)

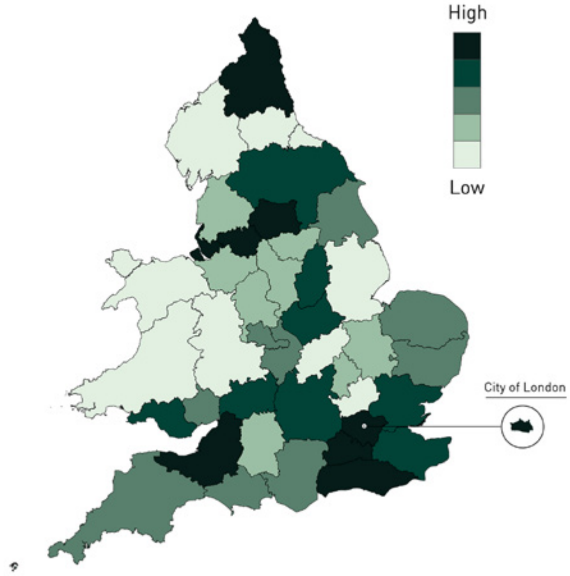
Data are also collected on numbers of **proceeds of crime offences**. Here data recorded under sections 327, 328, 329 of the Proceeds of Crime Act (2002) that are collected through Home Office statistics (labelled as 'profit or conceal proceeds of crime' offences) are collected. This is potentially a useful indicator of where money laundering activity might be occurring. For this reason, it is used in the analysis as a validation measure of the statistical model presented below (see STEP 6). Thus, if the model has any utility in predicting ML risk by territory, then a correlation between area ML risk as observed in the model and the distribution of POCA offences should be seen.

However, there are two main problems with this data source. First, low numbers of prosecutions are recorded across many areas and, where offences are recorded, this might be an **indication of police investigative activity rather than the actual extent of money laundering**. In order to increase the numbers, an average number per area is taken over a three year period. The highest actual numbers of ML offences (three year average) are in the Metropolitan police area (219 per year), West Yorkshire (175 per year) and Greater Manchester (94 per year). The mean area rate is 79 per 1m population with the highest rate per 1m population in the **City of London** (2,271 per million), West Yorkshire (77 per million) and Hertfordshire (76 per million).

In addition to proceeds of crime data, the **types of business that are subjected to money laundering regulations** (i.e. obliged entities) is also used as a validation measure. In the UK, as in other EU countries and also outside Europe, several business sectors are 'regulated' as they fall under AML obligations set by European Directive 849/2015 and corresponding national implementing measures (see Chapter 1). The analysis of the BvD data (see Figure 52)[98] indicated that the regulated sector businesses tend to concentrate in larger urban areas. For example, in total, **15% of businesses located in the City of London fell into these categories**, followed by 10% in the wider Metropolitan police area, 8% in West Yorkshire and Merseyside respectively.

98. The proxy variable for regulated businesses included financial services (business sub-sector K64), real estate (sub-sector L68), legal/accounting (sub-sector M69) and gambling (sub-sector R92).

Figure 52 – Location of AML regulated business sectors
% of regulated businesses on total per area



Source: University of Leicester elaboration

STEP 3 – DATA COLLECTION AND NORMALISATION

Similar to the threats variables, data relating to the vulnerabilities are also collected from a number of sources (see Annex A4). However, due to the paucity of data on business vulnerabilities, there is a reliance here on BvD data.

When conducting geographical analysis, the highest numbers of organised crime groups and predicate offences are most likely to be observed in the larger metropolitan areas. Therefore, **control variables** – such as resident area population, numbers of businesses and local rates of GDP – are used to control for differences in area size (see Annex A4 for details). While this allowed for meaningful area comparisons to be conducted across 42 police areas, it is problematic to compare predicate offences in the City of London to other police areas. The main reasons for this is that the City of London has a small population (of less than 10,000 residents), compared to an average of 1.2m across all other areas. Therefore, care has to be taken when interpreting data for the City of London to other areas. This is taken into account below as **two area risk models are developed** – one that includes the City of London and one that excludes this area.

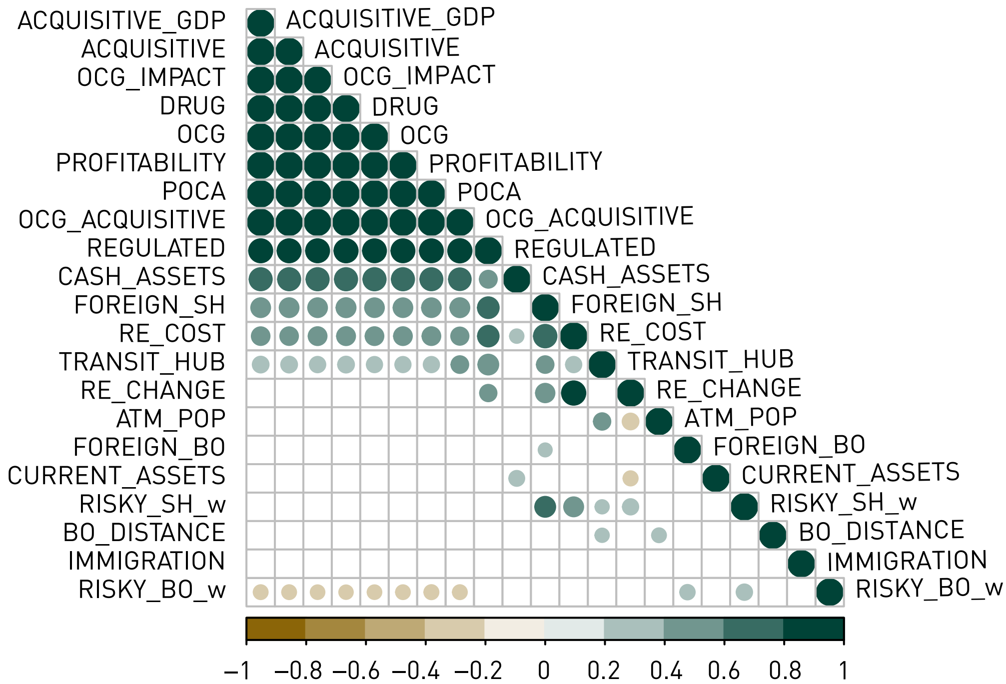
STEP 4 – DATA EXPLORATION AND CORRELATION ANALYSIS

All the risk factors discussed above are helpful in terms of understanding ML risk in the UK. However, if taken alone they do not give a very meaningful overview of the overall likely risk per area: therefore, it is necessary to **compare and combine them in order to have a proper measure of the overall ML risk**. This is the aim of the next steps (**steps 4-7**), where a composite indicator of ML risk, condensing all ML threats and vulnerabilities discussed so far, is constructed and validated. However, due to data limitations the model is only presented for England and Wales.

In order to begin to tease out where threats and vulnerabilities converge, some initial bivariate analysis is conducted. Figure 53 presents the strength and direction of the correlations between the variables for all 43 English and Welsh police areas. **The linear Pearson correlation** among the variables is identified in the correlogram below. Here, some strong correlations are observed between several variables with a number of the threats measures correlated with vulnerabilities measures. For example, the threats variables, organised crime groups per 100,000 population, organised acquisitive crime and drug seizures are all strongly correlated and these, in turn, are also correlated with vulnerability measures such as real estate costs and other control variables like the presence of regulated businesses. Other vulnerability variables such as transit hubs and risky shareholders are correlated with many variables including real estate costs and risky beneficial owners.

Figure 53 – Corrplot of proxies of ML risk factors at UK police area level

Pearson correlation – All 43 police areas



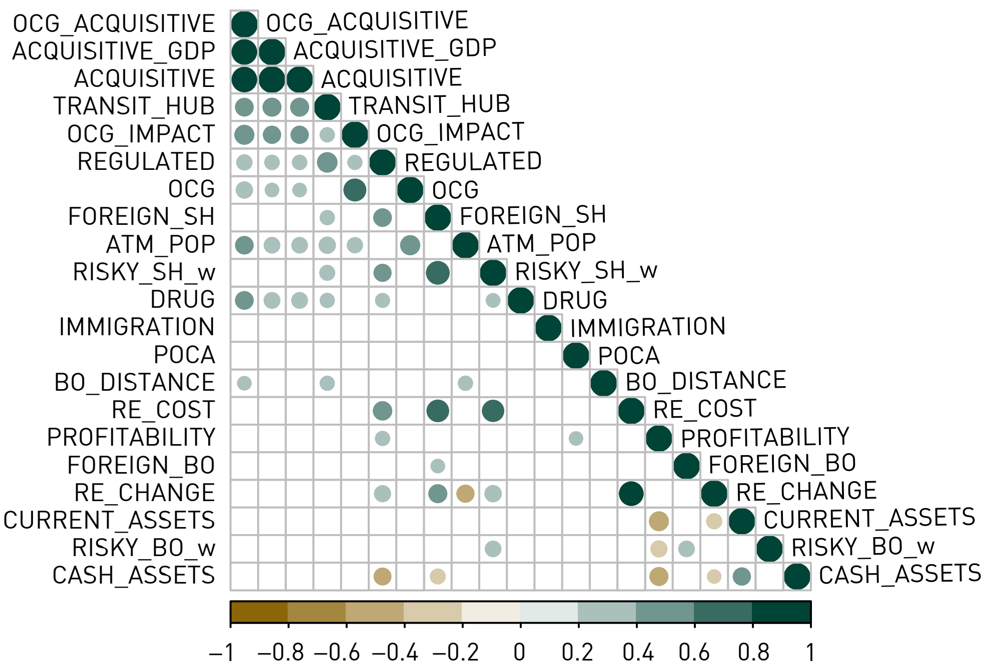
Source: University of Leicester elaboration

There is, of course, one area in the City of London that is considered to be an outlier.

Figure 54 presents the same linear Pearson correlation among the variables in the correlogram below with the City of London removed. The **City of London is merged with the Metropolitan Police Service** area, thus basing the analysis on 42 and not 43 areas. Here there are still a number of correlations between threat and vulnerabilities variables, although they are not as strong as before. For example, the number of organised crime groups per 100,000 population is correlated with the other threat variable of organised acquisitive crime and vulnerabilities variables such as the number of ATMs per population. Other variables, such as percentage of businesses in regulated sectors, is correlated with real estate costs and numbers of organised crime groups. The variable 'risky shareholders' is also correlated with real estate costs and percentage of businesses in regulated sectors.

Figure 54 – Corrplot of proxies of ML risk factors at UK police area level

Pearson correlation – 42 Police Areas (City of London grouped with Metropolitan Police)



Source: University of Leicester elaboration

STEP 5 – PRINCIPAL COMPONENT ANALYSIS (PCA)

To develop a composite indicator of ML risk, principal component analysis (PCA) is conducted. The main reasons for selecting PCA are these: (a) there are several indicators of threats/vulnerabilities in the dataset and (b) PCA allows these indicators to be grouped to understand what the main components of risk are. The following process is used:

1. For some variables, although they are identified as proxy measures of vulnerabilities in some literature, it is not entirely clear what the relationship is between the 'vulnerability' and the 'threat' – for example **ATM population and business profitability** – so these are therefore dropped.
2. Variables showing **non-significant linear correlation** with all other variables are dropped (such as organised immigration crime).
3. The variables of **money laundering offences** per population (POCA offences) and **regulated businesses** are also dropped because they are used to validate the final composite indicator (see STEP 7).

99. Principal component analysis is a multivariate data analysis technique used, in a similar way of other approaches (e.g. factor analysis), to reduce the information contained in large datasets into a smaller number of components (or factors, in factor analysis), each of them able to summarise a specific phenomenon explained by a range of correlated variables. For doing so, PCA uses an orthogonal transformation of the correlated variables into a set of principal components which are uncorrelated each other (OECD & JRC, 2008; Jolliffe, 2002).

This left a total of nine variables included in the model. Due to this low number of variables, three components are extracted. Table 49 presents the initial rotated component output from the model.

Table 49 – Principal component analysis. Matrix of rotated components
Varimax rotation. All 43 police areas in England/Wales

Variable	PC1	PC2	PC3
OCG	.983	-.091	-.003
DRUG	.985	-.062	.011
ACQUISITIVE_GDP	.984	-.087	.012
CASH_ASSETS	.799	-.082	.204
CURRENT_ASSETS	.105	.097	.737
BO_DISTANCE	-.031	-.087	.764
TRANSIT_HUB	.441	.408	.420
RISKY_SH_w	-.001	.893	-.134
RISKY_BO_w	-.273	.667	.153
SS Loadings	3.8	1.5	1.4
Proportion variance	0.44	0.18	0.15
Cumulative variance	0.44	0.62	0.77

Source: University of Leicester elaboration

The three principal components altogether explain around 77% of the variance observed in the dataset. Principal component 1 explained 44%, with principal component 2 and 3 explaining 18% and 15% respectively. The key components identified are:

- **Principal component 1 (PC1) – Serious and organised crime**: correlated to this component are the presence of organised crime groups (per 100,000 population), total acquisitive crime (per GDP), drug trafficking and seizures (per 100,000 population), cash intensive businesses and transit hubs. Overall, this component explains 44% of the variance in the model, and as is seen in the bivariate analysis, these variables are strongly correlated.
- **Principal component 2 (PC2) – Connections to risky jurisdictions**: The second main principal component relates to connections to risky shareholders, beneficial owners and transit hubs, which accounts for 18% of the variance in the model. As is observed in the bivariate analysis, the variables of risky shareholders and beneficial owners are correlated (Pearsons r=0.363), as are transit hubs and risk shareholders (r=0.391).
- **Principal component 3 (PC3) – Business opacity and cash-intensiveness**: The third principal component relates to cash intensity of businesses, average distance to beneficial owners and transit hubs. Thus, a connection is suggested between the 'cash intensity' of a business, business ownership structures, and being located in areas with international transit hubs. As is observed in the bivariate analysis, the variables of cash intensity 2 and 'average distance to beneficial owners' are correlated (Pearson's r=0.320) as are transit hubs and 'average distance to beneficial owners' (Pearson's r=0.301).

The same variables are then included in a model in which City of London is merged with the Metropolitan Police Service area. This model is also set to explain three principal components. The initial rotated component outputs from the model are presented in Table 50.

Table 50 – Principal component analysis: Matrix of rotated components

Varimax rotation. 42 Police areas. Model grouping City of London and Metropolitan Police

Variable	PC1	PC2	PC3
OCG	.221	.535	-.039
DRUG	.521	.313	-.006
ACQUISITIVE_GDP	.812	.056	-.148
TRANSIT_HUB	.731	.260	.038
CASH_ASSETS	-.156	-.009	.821
CURRENT_ASSETS	.263	.016	.796
RISKY_SH_w	.132	.810	-.137
RISKY_BO_w	-.171	.709	.394
BO_DISTANCE	.391	-.200	.256
SS Loadings	2.2	1.6	1.4
Proportion variance	0.27	0.19	0.15
Cumulative variance	0.27	0.46	0.61

Source: University of Leicester elaboration

It can be seen that when the City of London is grouped with Metropolitan Police, the three principal components combined explain around 61% of the variance observed in the dataset (from 77% in the previous model). Principal component 1 explains 27%, with principal component 2 and 3 explaining 19% and 15% respectively. The key variables can be grouped together to identify the key factors that explain the variation observed for each principal component. Therefore, the key components are:

- **PC1 (City of London grouped with Metropolitan Police) – Serious organised crime and transit hubs**: As with the previous model, acquisitive crime revenues are an important component in the model. Drug trafficking and seizures also remain important. However, the presence of international transit hubs also emerges as correlated to this PC. Indeed, the two variables of organised acquisitive crime revenues and drug transit hubs are highly correlated in the bivariate analysis (Pearson's r=.459), as are transit hubs and drug seizures (r=.499).
- **PC2 (City of London grouped with Metropolitan Police) – Connections to risky jurisdictions**: As with the previous model, connections to risky shareholders and beneficial owners remains grouped in a principal component. These two variables are highly correlated in the bivariate analysis (Pearson's r=.353).
- **PC3 (City of London grouped with Metropolitan Police) – Business cash intensity**: As with the previous model, the two proxies for businesses' cash intensity remain grouped in a principal component. Here the two measures of cash intensity explain 15% of the variance in the model and are correlated (Pearson's r=.429).

STEP 6 – AGGREGATION AND COMPOSITE INDICATOR CONSTRUCTION

The principal components identified through the PCA are combined to provide a synthetic composite indicator of ML risk. In particular, as in the Italian and Dutch analysis, PCs are put together in **linear combination using as weights the proportion of the model variance** explained by each component (see Chapter 2, 3 and Annex for more details). This allows one of the most frequent gaps of current indicators to be addressed - that individual risk dimensions are combined using discretionary weights, which ultimately affect the final scores and rankings.

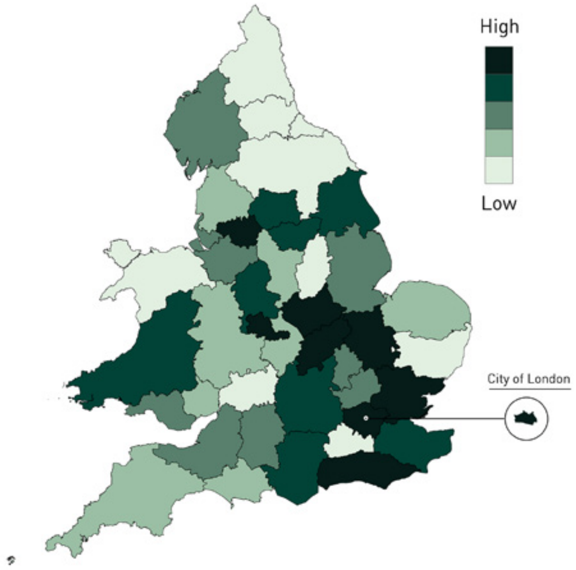
The table below presents the overall composite indicator for the top ten most risky and the ten least risky UK areas; and the contribution of each of the three principal components to the indictor for the model that includes the City of London (Model 1) and the model that groups it with Metropolitan Police area (Model 2). As Table 51 shows, the composite risk score (right hand column), is **highest for the City of London, followed by the Metropolitan Police area and Greater Manchester**. The geographical distribution is presented at Figure 55.

Table 51 – Top 10 most risky and 10 least risky areas according to the final ML Risk Composite indictor
Model 1 – All 43 police areas

	PC1	PC2	PC3	ML Risk Composite Indicator
	Serious and organised crime	Connections to risky jurisdictions	Business opacity and cash-intensity	
London, City of (EC)	100.0	52.4	58.0	**100.0**
Metropolitan Police	0.0	100.0	87.5	**31.4**
Greater Manchester	5.8	54.2	97.3	**21.2**
West Midlands	4.7	57.0	96.5	**21.2**
Essex	5.9	44.0	89.5	**16.6**
Leicestershire	6.9	43.8	78.0	**15.8**
Cambridgeshire	5.1	49.8	61.6	**14.3**
Northamptonshire	4.1	44.6	80.8	**14.0**
Sussex	0.5	49.3	91.7	**13.9**
Dyfed-Powys	15.7	8.3	100.0	**13.9**
West Mercia	7.2	25.2	62.0	**7.3**
North Wales	12.7	0.0	92.6	**7.1**
Cleveland	7.7	25.0	52.2	**6.3**
Surrey	4.1	47.7	9.8	**5.7**
Nottinghamshire	6.7	32.8	32.8	**5.6**
Northumbria	9.3	23.5	35.8	**5.0**
Suffolk	6.0	30.0	36.3	**4.5**
North Yorkshire	7.2	15.8	60.1	**3.6**
Durham	7.4	28.0	19.7	**2.8**
Gloucestershire	4.6	34.5	0.0	**0.0**

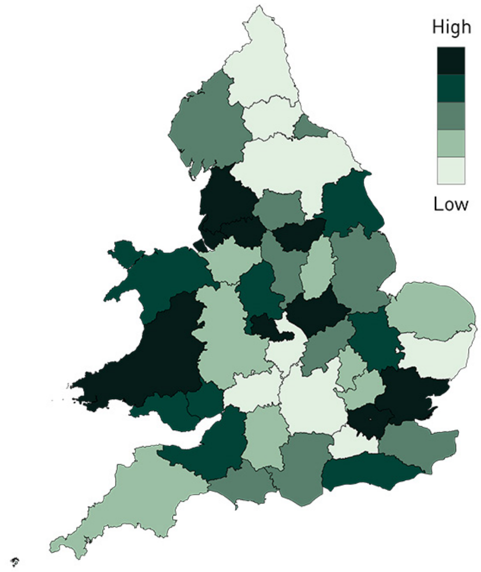
Source: University of Leicester elaboration

Figure 55 – ML risk across UK areas (all 43 police areas)



Source: University of Leicester elaboration

Figure 56 – ML risk across UK areas (42 police areas, City of London grouped with Metropolitan Police)



Source: University of Leicester elaboration

Table 52 – Top 10 most risky, and 10 least risky areas according to the final ML Risk Composite indictor
Model grouping City of London and Metropolitan Police

	PC1	PC2	PC3	ML Risk Composite Indicator
	Serious organised crime and transit hubs	Connections to risky jurisdictions	Business cash intensity	
Metropolitan Police + City of London	95.6	40.4	100.0	**100.0**
Greater Manchester	100.0	43.0	22.4	**75.3**
Dyfed-Powys	45.3	100.0	12.0	**67.9**
Leicestershire	91.7	35.5	14.9	**64.0**
Lancashire	63.9	54.0	31.1	**63.0**
West Midlands	82.4	35.4	26.6	**62.9**
Merseyside	67.2	57.5	15.7	**60.9**
South Yorkshire	79.7	40.7	12.0	**58.5**
Essex	72.0	42.6	15.8	**56.4**
Sussex	34.6	56.9	49.9	**54.3**
Norfolk	14.5	50.6	18.1	**27.8**
West Mercia	8.9	49.3	26.7	**27.1**
Warwickshire	23.6	25.6	30.5	**25.4**
North Yorkshire	25.0	41.6	5.7	**25.0**
Thames Valley	20.7	17.5	44.7	**24.9**
Northumbria	22.6	24.1	8.7	**16.0**
Durham	27.0	14.0	10.5	**14.3**
Suffolk	2.4	22.3	19.7	**7.5**
Surrey	0.0	0.0	37.5	**1.6**
Gloucestershire	0.7	3.4	27.5	**0.0**

Source: University of Leicester elaboration

In Table 52 the composite risk scores are presented for 42 police areas (City of London grouped with Metropolitan Police). When the City of London is excluded from the analysis, the Metropolitan police area and Greater Manchester become the top two most risky locations. The geographical risk is visually presented at Figure 56.

It should be noted that the composite risk scores for **Models 1 and 2 are significantly correlated** (Pearson's r= .901). This suggests that even when the City of London is grouped with Metropolitan police, the area ranks are similar (this is supported by a Spearman rank order score of .734).

STEP 7 – SENSITIVITY ANALYSIS AND VALIDATION

Validation of the risk indicator is performed in two ways (as in the Italian provincial analysis – see Chapter 2):

- on the one side, it is compared with **alternative measures of money laundering** at area level;
- on the other side, a **sensitivity analysis** is carried out calculating the composite indicator again introducing some changes to the methodological parameters (e.g. the type of rotation in the PCA, type of normalisation, etc.).

Comparison with alternative ML measures

In Italy the final ML risk indicator is compared with the regional distribution of STRs to see how they correlate. Due to the paucity of SARs data at area level in the UK, it is difficult to adopt the same approach. However, the scores are tested against two other indirect measures of ML and ML risk – **money laundering offences** per 1m population and percentage of businesses within the local business population that fall under AML obligations (i.e. ***regulated sectors***). Theoretically, if the composite score is a good measure of overall risk, then one might expect to see this score correlate with both of these measures – at least with the number of POCA offences.

The Pearson correlation coefficients (Table 53) show that for Model 1 (including the City of London) both variables are highly correlated – respectively r= .826 for ML offences and r=.772 for regulated sectors. However, once the City of London is omitted, the strength of the correlations alter. There is still a correlation (weak but still statistically significant correlation (r=311: sig .045) between high risk businesses and the composite indicator. However, the relationship between the composite indicator and money laundering offences is no longer statistically significant when the City of London is not treated separately.

Table 53 – Validation of models: correlation of composite scores to validation variables

		Model 1 (all 43 police areas)	**Model 2 (42 areas - City of London grouped with Metropolitan Police)**
Money Laundering offences average per 1m pop	Pearson Correlation	.826**	-.026
Regulated businesses	Pearson Correlation	.772**	.311*

** = significant at 99% level (2-tailed); * = significant at 95% level (2-tailed)

Source: University of Leicester elaboration

Sensitivity analysis

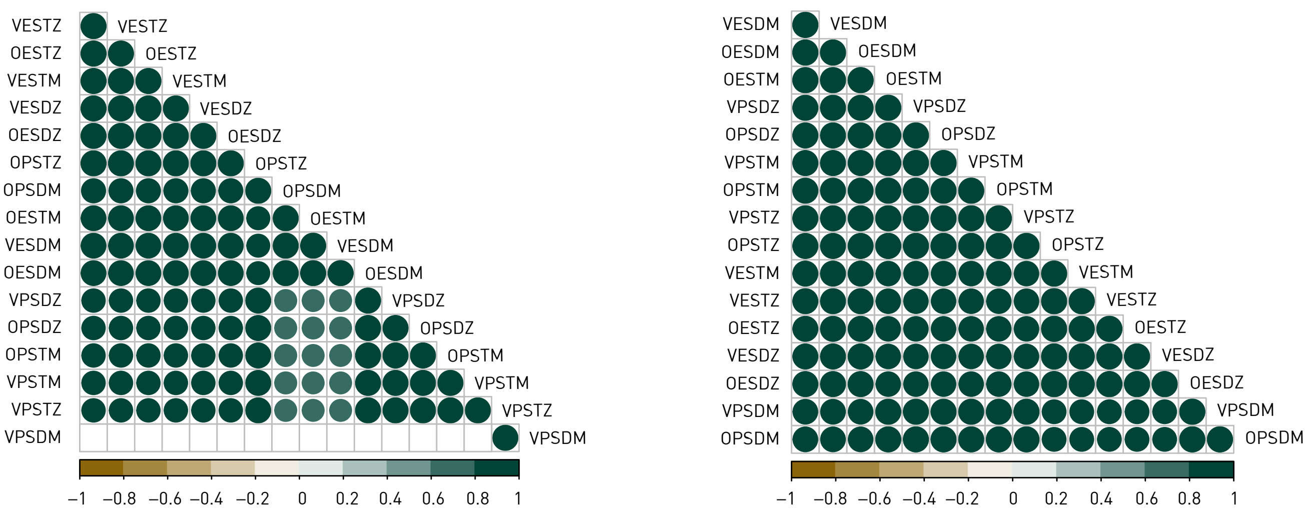
Similar to the analysis conducted at territory level for Italy (see Chapter 2), sensitivity analysis is performed in order to ascertain if changes in the methodology regarding, for example, weighting, aggregation and normalisation of the variables in the PCA **affect the overall result and ranking of risk**. The main methodological options used to construct the indicator are outlined in Chapter 2 (see also Annex for details). In relation to the UK, the methodological approaches are run for both the models (including and excluding the City of London).

Figure 57 presents the correlation for the composite risk indicators for all areas and then Figure 58 does the same for all areas excluding the City of London (grouped with Metropolitan police) when these different methods are applied.

Sensitivity analysis is also applied to see whether the selection of variables affects the robustness of the analysis. Figures 58 show the correlation matrix among the composite indicators scores produced after dropping one selected variable at a time from the final models (Model 1 and Model 2).[100]

As can be observed above, most of the indicators produced by the sensitivity analysis are highly and positively correlated. Indeed, most have Pearson correlations of above 0.9, which suggests that the **changes in the methodology do not affect the overall result** and ranking. The risk ranks of the all the police areas included in the sensitivity analysis (when the City of London is included as compared to when it is not included) is presented at Annex A4.

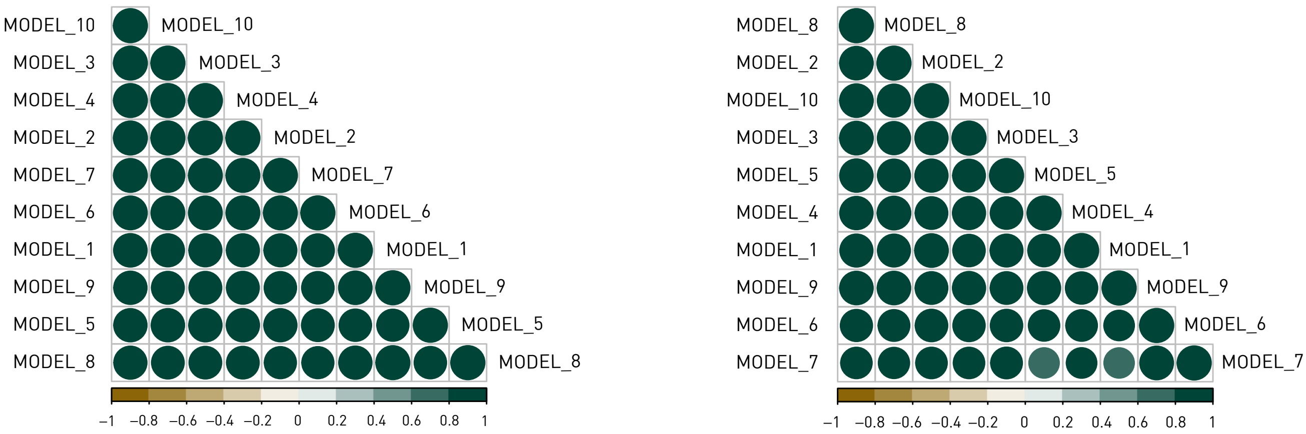
Figure 57: Correlation among ML risk composite indicators after applying different methodologies
All 43 police areas (left); 42 areas - City of London grouped with Met Police (right). VPSTM = Final Model



Source: University of Leicester elaboration

100. In each matrix, the variables that are omitted are: Model 1: all variables in final model are included; Model 2: Numbers of organised crime groups; Model 3: Drugs crimes; Model 4: Acquisitive crimes; Model 5: Presence of transit hubs; Model 6: Business cash assets; Model 7: Business current assets; Model 8: Business ownership links to shareholders in risky jurisdictions; Model 9: Business ownership links to beneficial owners in risky jurisdictions; Model 10: Average distance to beneficial owners.

Figure 58: Correlation among ML risk composite indicators after dropping one variable at a time
All 43 areas (left); 42 areas - City of London grouped with Met Police (right)



Source: University of Leicester elaboration

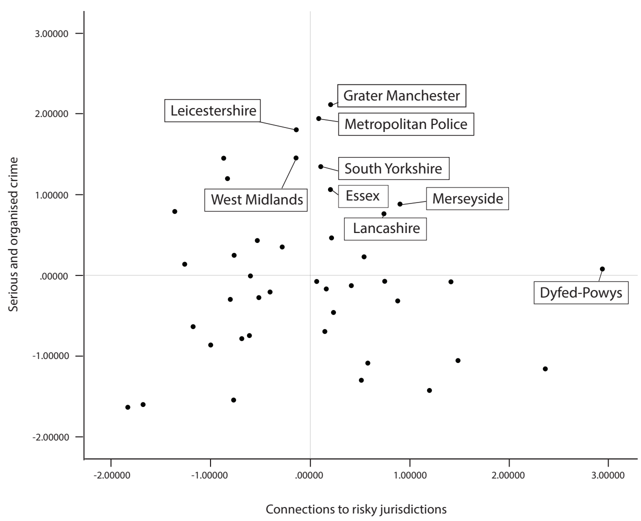
Concluding remarks

The composite indicator presented in this section identifies a potentially useful methodology to develop a better understanding of money laundering risk in the UK. It attempts to **compress a complex issue into a composite measure**, which might be useful for policy makers in terms of identifying risky locations.

However, this analysis does offer the potential to begin to understand how **each component in the model contributes to money laundering risk**. An illustration of this is presented in the scatterplot (Figure 59). This plots the relationship between the principal component 1 and the principal component 2 as identified in the area model merging the City of London with Metropolitan Police (this is treated as it is an outlier). The top ten areas that are identified as having the highest composite risk scores as presented in Table 52 respectively are labelled. The scatterplot plot suggests that:

1. For two areas (Dyfed Powys and Sussex) it is connections to risky jurisdictions that push the areas into the high risk group;
2. For six areas (Metropolitan, Greater Manchester, South Yorkshire, Essex, Lancashire and Merseyside) a combination of serious/organised crime threats, transit hubs and connections to risky jurisdictions push the areas into the high risk group;
3. For two areas (West Midlands and Leicestershire) it is predominantly exposure to serious and organised crime that pushes the area into the high risk group.

Figure 59: A comparison of PC1 v PC2: organised crime vs. connections to risky jurisdictions
(42 areas - City of London grouped with Met Police)



Source: University of Leicester elaboration

4.3 Analysis at business sector level

ML risk at business sector level in the United Kingdom: problems encountered

In Italy and in the Netherlands, the degree of ML risk is also calculated across all the business sectors of the legitimate economy (see chapters 2 and 3). Within the UK, while proxies for ML vulnerabilities are available (and are used also in the area level analysis, see above) establishing the extent of **money laundering threats at business sector level is more problematic.** Throughout the course of this study, a number of potential sources are identified, though none are considered robust enough to use as the basis for analysis. In the table below the main identified sources are presented and their limitations outlined.

A large volume of data are routinely collected in the form of the Suspicious Activity Reports that regulated businesses must issue as part of their compliance with ML regulations. However, such data are limited for three principal reasons. First, many of the reports are made by businesses in order to be compliant with the ML regulations and do not represent actual attempts to launder money (Home Office, 2016a). Second, not all business sectors are covered by the regulations. Third, is it difficult to conduct analysis using the current SARs system that allows identification of the business type that a SAR is made in relation to.

Table 54 – Main Potential UK sources on ML or OC threats to businesses

Potential Source	Sector Coverage	Methodology	Limitations
Suspicious activity reports	Regulated sectors	Obliged entities submit SARs to FIU	May indicate ‘compliance’ rather than actual money laundering activity
			Limited number of sectors (only those under AML obligations)
			Impossible to identify ‘source’ business type
National Risk Assessment	Regulated sectors	Assessment of threats and vulnerabilities using MoRiLE*	Limited number of sectors
			Unclear methodology
Commercial Victimisation Survey	7 sectors – agriculture, construction, information, wholesale, accommodation/ food, arts/entertainment, manufacture and transport	Surveys with businesses	Limited sector coverage
			Based upon business owners’ perceptions of being victim of organised crime, rather than ML
Organised Crime Portfolio	All sectors	Media Reports	Sample dependent upon media reporting and focuses on organised crime rather than ML

* MoRiLE - Management of Risk in Law Enforcement: a risk assessment tool developed by the UK National Crime Agency

Source: University of Leicester elaboration

The limitations identified with SARs data also impacted upon the robustness of the recent UK National Risk Assessment (HM Treasury, 2015). References are made in the NRA to the **weakness of SARs data**, and it is clear that the assessment of threats to businesses is hampered by the limited sources of data available. Although the NRA calculates risk scores, these are only for regulated sector business (see NRA: 2015. p 12) and are largely based on expert opinion and intelligence data, rather than any systematic analysis of known threats to businesses (the methodology used in the UK NRA is explained in detail at Annex A4). The issues with the methodology used in the NRA made it difficult to replicate for the purpose of this study. Indeed, while not all business sectors are included in the risk assessment, it is also difficult to establish how risks are calculated for those that are included.

Other potential sources of threats are identified, but also these had several limitations. In the absence of any meaningful data on money laundering, attention turned to data in relation to organised crime infiltration of businesses. Indeed, recent sweeps of the **Commercial Victimisation Survey** (See Home Office, 2016b), which covers England and Wales, have asked business owners about the extent to which they feel crimes committed against their businesses are the work of organised criminals. While this provides some potentially useful data, it is questionable whether business owners would provide an accurate indication of levels of organised crime against their business. Also, to date, the **CVS has only covered seven business sectors** – agriculture, construction, information, wholesale, accommodation/ food, arts/entertainment, manufacture and transport. So there is no sector coverage of financial/ or other regulated sectors businesses (except for gambling).

There has been one other notable attempt to measure the extent of organised crime infiltration against business in the UK. In the recently published Organised Crime Portfolio (OCP) report, businesses are categorised by Wall & Chistyakova (2015) according to levels of OC infiltration (below – in Table 55 – the categorisations across business sectors are outlined). However, the source data for the categories used in the OCP are based upon 'open sources' – such as media reports. This is problematic because it focuses on where there has been media activity, rather than systematic reports of organised crime or money laundering.

Table 55 – OCG infiltration of businesses in the UK

Business sector	References to organised crime infiltration
Wholesale/retail	>26
Hotels, bars and restaurants	
Clubs and gambling activities	
Transport	17 - 26
Financial	
Personal services	7-16
Support services	
Construction	
Manufacture	1-6
Waste and scrap	
IT services	
Real Estate	
Legal	
Public admin	
Hospitals	
Agriculture and fishing	0
Mining and quarrying	
Energy Supply	
Education	

Source: University of Leicester elaboration on Project ARIEL report (Savona & Berlusconi, 2015, p. 71)

While some attempts have been made to count suspicious activities across regulated business sectors, identify the risks against the regulated sectors or identify the types of businesses where there is organised crime infiltration, most of the data generated in the UK are of limited practical use when trying to identify threats to businesses. This has clear implications when trying to develop a risk-based approach because no clear measures of threats across all business sectors (or ideally business sub-sectors) exist.

This is something that needs to be considered, and it is of particular note that the UK anti-money laundering action plan includes a **programme of radical reform for the SARs regime**, which is projected to be completed in October 2018 (Home Office, 2016a). A significant strand of the reforms in terms of identifying threats to business from SARs data is the shift from a transactions-focused regime to a system targeting individuals and organisations that pose the highest ML risk which, together with the intended development of a replacement SARs IT system, may address the limitations of the data that are currently available.

4.4 Research and policy implications

This chapter has conducted analysis of ML threats and vulnerabilities. It has developed a **composite indicator of ML risk at sub-national level** (across 43 police areas of England and Wales – it was not possible to extend the analysis to Scotland and Northern Ireland due to lack of workable data). It is identified that developing proxy measures for money laundering risks is difficult in the United Kingdom because of the paucity of appropriate data. While it is possible to develop an area level composite indicator, data limitations mean this is not possible for the business sector.

What is the added value of this analysis?

While this analysis is not definitive, it provides an illustration of how measures of threats and vulnerabilities could potentially be used to identify high risk locations. This **complements the existing UK NRA** (HM Treasury, 2015), and the methodology could potentially be used in further national risk assessment exercises because the approach:

- is both transparent and easily replicated;
- adopts a sub-national perspective (across 43 police force areas), while the current UK NRA only has a national perspective. Where possible, analysis is also conducted across all business sectors, whereas the UK NRA focuses only on regulated sector businesses;
- condenses the complex phenomenon of money laundering – which compromises multiple threats and vulnerabilities – into a single composite indicator;
- conducts detailed analysis of vulnerabilities to money laundering – such as business ownership structures (both shareholding and beneficial ownership) – that have been hypothesised as vulnerabilities, but not, until now, subject to any meaningful empirical analysis.

Weaknesses of the UK analysis

The findings presented here are part of a pilot study. Therefore, this is the first time that researchers have attempted to assess money laundering risks in the UK using the risk-based methodology. This has generated a number of challenges and issues that any researchers attempting a similar exercise in the future should bear in mind:

- the approach is **reliant on the availability of data** that can be developed into proxy measures of threats and vulnerabilities. Indeed, a composite indicator of ML risk for business sectors could not be developed because there are no reliable measures of ML threats;
- the methodology cannot account for '**known emerging threats**' – such as virtual currencies – where no quantifiable data exist at present;
- the model is unable to account for other factors – such as **vulnerabilities in AML regulation** – that might be key drivers of ML risk, but are difficult to measure at sub-national or business level;
- at the sub-national level, care has to be taken when interpreting such a model because there is an underlying assumption of a spatial association/connection between money laundering threats and vulnerabilities. It is, of course, plausible that **money may be laundered in locations that are not spatially close** to where the proceeds of crime are generated;
- as mentioned, the model focuses on England and Wales only because of the paucity of data on risk factors (e.g. organised crime and other predicate offences) in Scotland and Northern Ireland.

Implications of this research

The risk-based approach is of potential benefit to any **policy, law enforcement or academic bodies** trying to gain better understanding of money risk at a national or sub-national level across the UK. Those developing future NRAs within the Home Office and Treasury might benefit from utilizing the approach outlined. There are, of course, also potential ramifications in relation to the UK AML action plan (Home Office, 2016a). A key issue raised in the plan related to the reform of the current SARs regime. Indeed, collecting data that might better inform our understanding of the threats at both sub-national level and across all business sectors is essential if the risk-based approach is to be utilised in future.

While the risk-based approach has clear potential to help develop evidence-based policies, there are a number of clear issues that need to be considered:

1. **Improving the availability and quality of data**: as outlined above, the development of the area level and business sector level models are limited by the lack of data in relation to threats and vulnerabilities. Considering the UK's commitment to evidence-based policy and also its commitment to completing regular national ML risk assessments, now would be a good time to consider (a) what data need to be routinely collected for the purpose of these assessments and (b) how they can be collected in a format that can be easily subjected to quantitative analysis.
2. **Whether the risk-based approach should be utilised in the UK NRA**: consideration might be given as to whether the risk-based approach should be adapted for the UK NRA. At present, the UK NRA lacks a transparent methodology and does not conduct clear analysis of threats and vulnerabilities. The utilisation of the risk-based approach might, therefore, provide future NRA's with a clearer methodological and analytical framework.
3. **The potential to draw upon and develop international knowledge about how to complete risk-based assessments**: as more nations begin to utilise the risk-based approach in order to complete ML risk assessments, there will be the potential to exchange international knowledge about ML risk, the development of the risk-based methodology and which sources of data can be best developed and used to populate such a model. Indeed, the UK might both benefit from the development of international 'good practice' in relation to the use of the risk-based approach and also be able to inform good practice.

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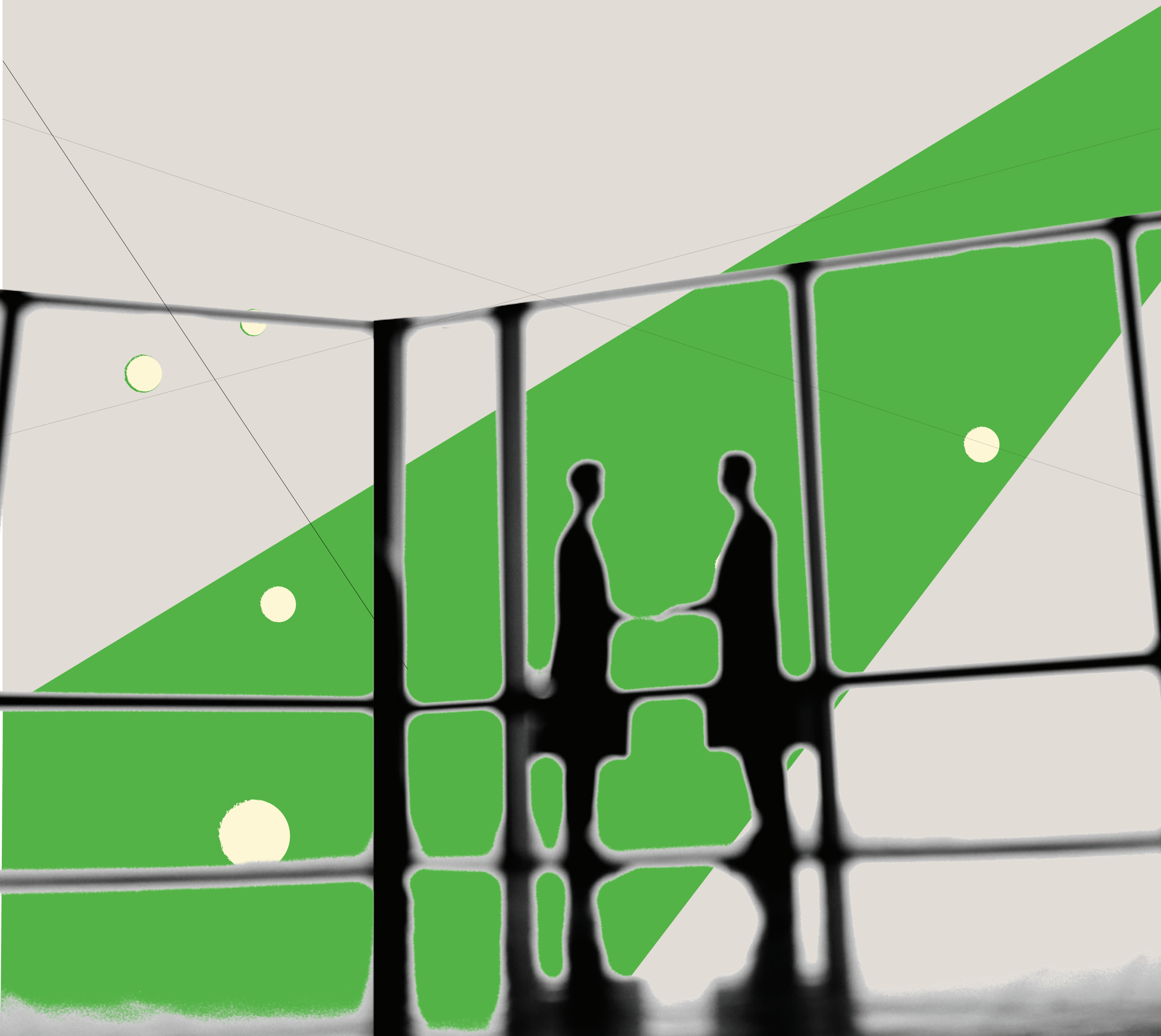
5. Focus: Opacity of business ownership in Italy, the Netherlands and United Kingdom



Opacity of business ownership is one of the key ML vulnerabilities of the IARM risk assessment model. Thanks to the access to the largest available dataset on business ownership data at global level (provided by BvD), and to the development of innovative proxies for business opacity, IARM has carried out an analysis of this issue:

- in Italy (Chapter 2)
- in the Netherlands (Chapter 3)
- in the UK (Chapter 4)

This chapter provides a further in-depth investigation of these data, comparing results across countries and business sectors and identifying major patterns and trends. As in the country analysis, the opacity of business ownership is analysed with respect to two sub-dimensions:

- The level of complexity of businesses' ownership structure as such;
- The volume of business ownership connections with shareholders and BOs from risky jurisdictions.

The global debate on business ownership transparency

In recent years, an international consensus has emerged that the increased transparency of business ownership information is of key importance for tackling the misuse of companies to launder the proceeds of crimes (FATF, 2014a; UK Department for Business Innovation & Skills, 2016). This approach is at the basis of FATF Recommendation 10, which stimulates financial institutions and obliged entities to:

"Identifying the beneficial owner, and taking reasonable measures to verify the identity of the beneficial owner, such that the financial institution is satisfied that it knows who the beneficial owner is. For legal persons and arrangements this should include financial institutions understanding the ownership and control structure of the customer" (FATF, 2012, p. 16).

The approach has found support within the G8 (G8, 2013) and the G20 (G20, 2014); and it has been further acknowledged by the EU Fourth AML Directive, which requires MS to set up a central public register of beneficial owners accessible to a variety of stakeholders (EC, 2015). The problems related to the opacity of business ownership have been highlighted by a vast academic and institutional literature, in regards to money laundering (e.g. Unger, Ferwerda, van den Broek, & Deleanu, 2014; Riccardi & Savona, 2013; WEF, 2012; Steinko, 2012; Blum et al., 1999), to tax evasion and grand corruption (e.g. Reuter, 2012; de Willebois et al., 2011) and also by numerous NRAs worldwide (e.g. HM Treasury, 2015; U.S. Department of the Treasury, 2015).

Despite being a central issue at policy-making level, the research focus on this topic has been weak, first of all due to lack of data. IARM carries out the first large-scale investigation of the opacity of business ownership structure in Italy, the Netherlands and UK using a set of innovative proxies and data.

5.1 Complexity of business ownership structure

As discussed in previous chapters, a good measure of business ownership complexity is the so-called **BO distance**, provided by BvD, which measures the average number of 'steps' which separate a company from its BO(s).[101] The average BO distances in the three IARM countries are the following:[102]

- Italy 1.3
- Netherlands 1.7
- United Kingdom 1.6[103]

Of the three countries, Italy has the lowest average BO distance, suggesting that for most companies there is a **direct control**. As mentioned, Italy has also a very high number of individual enterprises, confirming the direct nature of business ownership. The higher values of the Netherlands and the UK could be, as mentioned in chapters 3 and 4, proxies for the higher number of **multinational companies registered in those countries** – either for tax optimisation purposes or for other reasons.

However, also within the same country the values vary depending on the **region or the sector considered**. Table 56 below reports the first 5 areas in Italy and in the UK per BO distance.[104] In Italy, ranking first are areas close to borders (such as Imperia, Savona and Bolzano), large urban and economic centres (Milano). Catanzaro and Imperia are also characterised by high levels of underground economy/tax evasion and of OC infiltration (see Chapter 2). In the UK, the first two areas are **Channel Islands and Isle of Man**, which are well known off-shore financial centres. In these areas, it is necessary on average to investigate almost **four layers of control** before identifying the relevant beneficial owners(s).

Table 56 – Average BO distance at sub-national area level in Italy and UK

Top 5 areas by value. NUTS 3 classification. Last available year

ITALY	BO distance	UNITED KINGDOM	BO distance
Imperia	1.49	Channel Islands	3.70
Catanzaro	1.45	Isle of Man	3.40
Savona	1.40	South Yorkshire	2.48
Bolzano-Bozen	1.40	Greater Manchester	2.00
Milano	1.39	Norfolk	1.68

Source: Transcrime – UCSC elaboration

101. BOs in BvD definition are the natural person(s) who ultimately own or control an entity. They are identified by BvD reconstructing the ownership chain until finding natural persons holding above a certain shareholding. For the purpose of this study it has been decided to set the minimum threshold at 10% at the first level of company ownership chain and 10% at further levels. The adopted threshold is lower than EU Directive definition (25% threshold) but allows for a more comprehensive analysis. When BO distance equals 1, the company is directly controlled by its BO(s) (see Annex for details).

102. BO distance at country level is here calculated as the average of the BO distances of the business sectors at the NACE division level. Please note that it could differ from the BO distance calculated as the average BO distance of country regions. It has been decided to adopt this approach in order to compare the score among the three countries more properly, as the number, size and nature of areas could change from country to country, while the sectorial classification is the same. In Italy the average BO distance of the 110 provinces is 1.21 and in the UK is 1.59 (see Chapter 2 and 4).

103. The average BO distance is 1.5 after excluding Channel Islands and Isle of Man (see below)

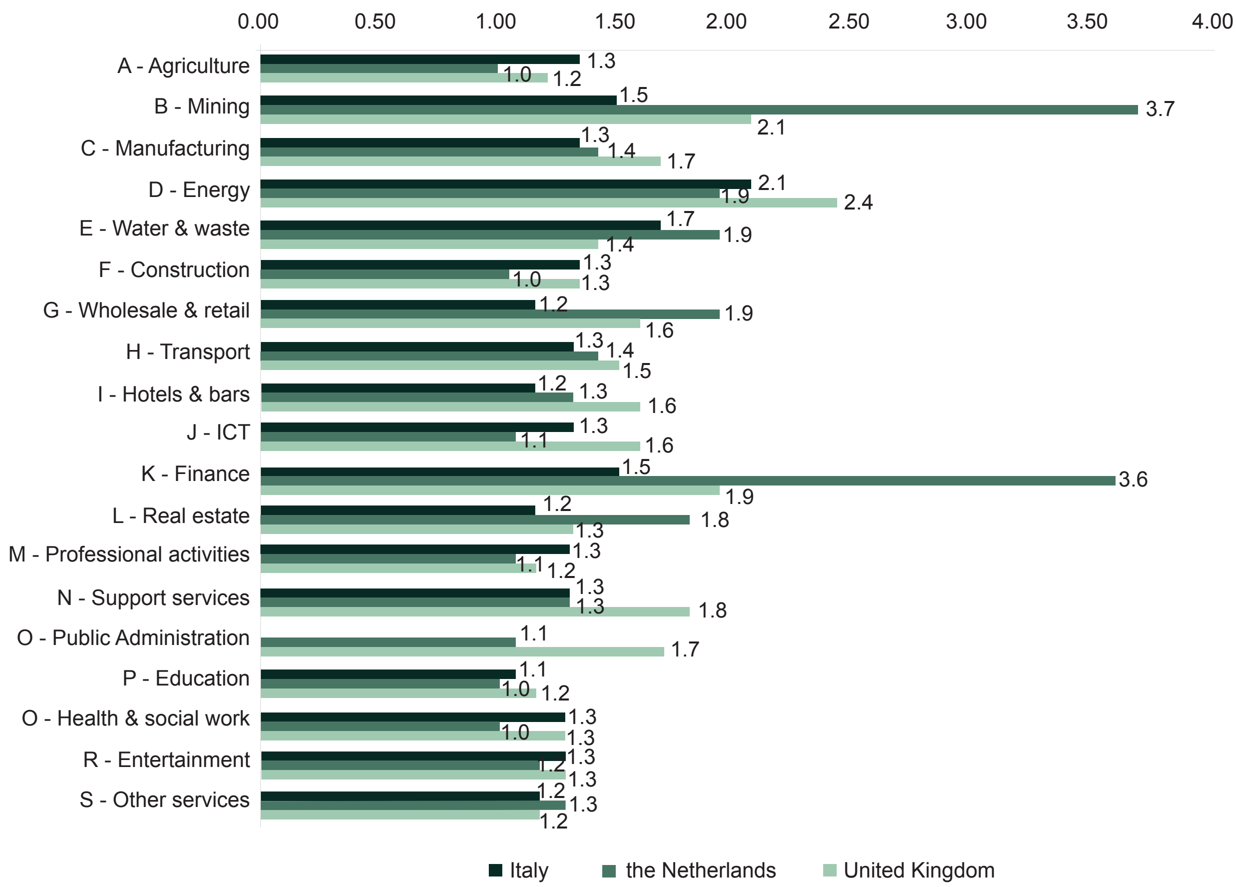
104. The analysis is not performed at sub-national area level (NUTS 3) in the Netherlands because not meaningful given the small country size and the administrative nature

The analysis at business sector level shows that NACE sections **B (Mining & quarrying), K (Financial and insurance activities), E (Water supply, sewerage, waste management and remediation activities) and D (Electricity)** score highest in all the three countries analysed. As mentioned, these business sectors are characterized by a high market concentration, high barriers to entry, and a larger number of large companies. These factors may increase the **number of multinational enterprises**, thus *de facto* increasing the BO distance. In particular the highest values are those of mining (which includes also oil & gas extraction) and finance in the Netherlands, followed by energy in the UK. Energy is also the sector with the highest BO distance in Italy. Among the lowest are the public sector (O), education (P) and agriculture (A).

However, as mentioned in previous chapters, in order to identify the **actual anomalies in terms of business complexity**, the presence of multinational companies is controlled by weighting the average BO distance with a proxy for company size. After this operation, sections B, D, E and K rank much lower, while other sectors emerge.

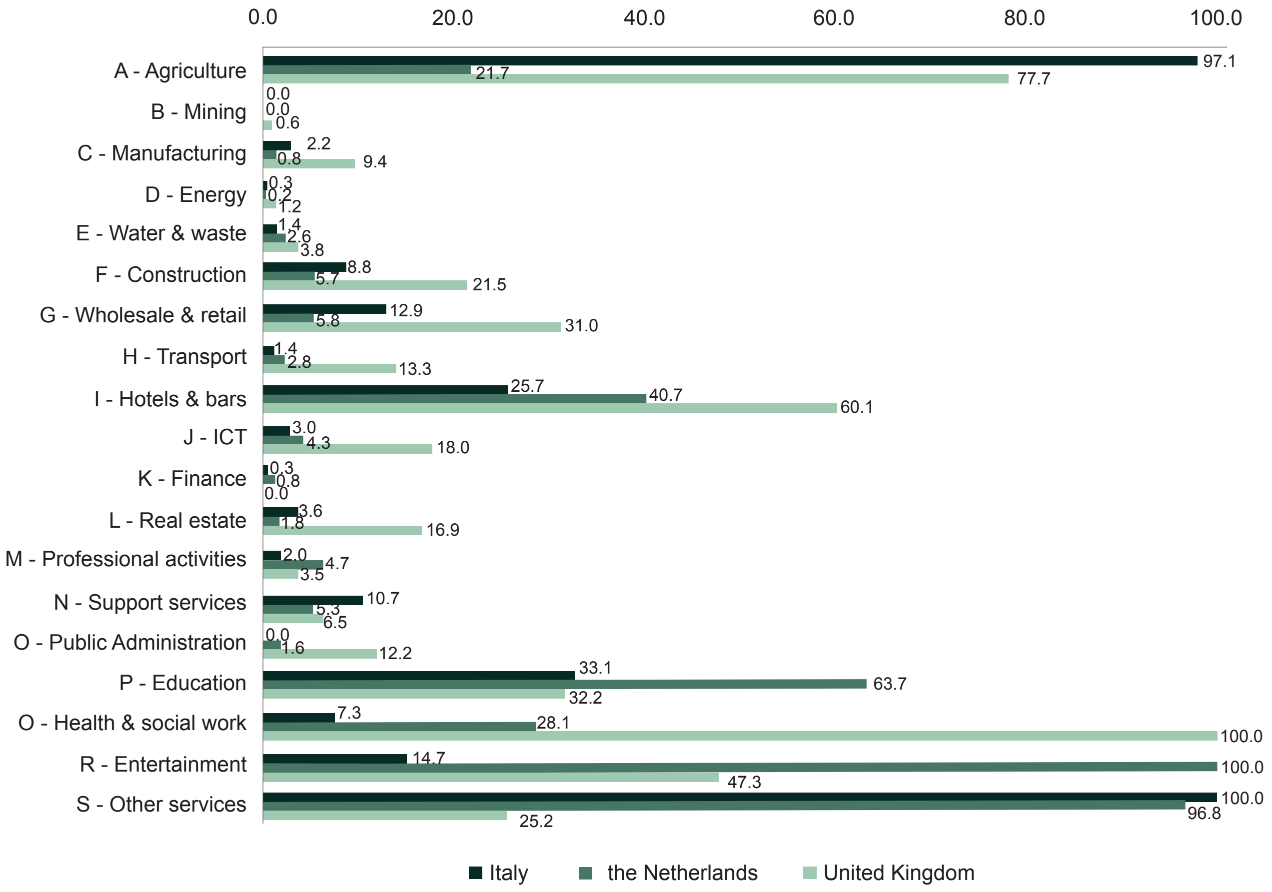
In Italy, S (Other Services) and A (Agriculture) rank highest. In the Netherlands, Sections R (Entertainment – including also gaming, gambling and other leisure activities), S (Other services), P (Education) and I (Accommodation) stand out. In the UK, sections Q (Health and social work), A (Agriculture) and I (Accommodation) now score high. The analysis also highlights some similarities among the three countries: for example, division **S 95 (Repair of computers and personal and household goods) and I 56 (Food and beverage service activities)** appear in the top five in each of the three countries. Also **S 96** (Other personal activities) ranks high in two out of three countries.

Figure 60 – Average BO distance per business sector by country (Italy, the Netherlands and UK)
Excluding NACE sections T and U (in all the three countries) and O (public sector) in Italy



Source: Transcrime – UCSC elaboration

Figure 61 – Average BO distance per business sector by country (Italy, the Netherlands and UK)
Weighted by average company size. 0-100 scale. Excluding NACE sections T, U and O (in Italy).



Source: Transcrime – UCSC elaboration

Table 57 – Average BO distance per business sector by country (Italy, the Netherlands and UK)
Weighted by average company size. Top 5 NACE divisions

Rank	Italy	the Netherlands	United Kingdom
1	S 95. Repair of computers and personal and household goods	R 90. Creative, arts and entertainment activities	A 02. Forestry and logging
2	S 96. Other personal service activities	S 96. Other personal service activities	S 95. Repair of computers and personal and household goods
3	A 01. Crop and animal production, hunting and related service activities	S 95. Repair of computers and personal and household goods	I 56. Food and beverage service activities
4	A 03. Fishing and aquaculture	R 93. Sports activities and amusement and recreation activities	M 75. Veterinary activities
5	I 56. Food and beverage service activities	I 56. Food and beverage service activities	Q 86. Human health activities

Source: Transcrime – UCSC elaboration

105. The company size proxy has been calculated using the ratio between the total number of companies in a certain sector j and the total assets within the same sector (see Annex for further details).

106. The downside of weighting BO distance by company size is that the resulting value cannot be read in the same way as before. In the chart, it is normalised in the 0-100 scale but it cannot no more be interpreted as number of steps separating a company from its BOs

5.2 Business ownership connections with risky jurisdictions

Although the study of cross-border interlocking ownerships and directorships is still in its infancy, mainly due to the paucity of data, it can be assumed that the share of foreign owners of companies registered in a certain area (or sector) may depend on a variety of drivers (Ferwerda & Riccardi, 2016):

- the presence of **foreign citizens resident** in that area (who may decide to set up a business);
- the role played by that area (or sector) in the **international trade** network;
- the capacity to attract **foreign direct investments** (FDI);
- the **efficiency of bureaucracy and institutions,** as entrepreneurs may decide to incorporate a business in a certain country because it is easier, quicker and more convenient (The World Bank, 2017);
- the presence of **lower tax rates** and of **corporate tax incentives** (OECD, 2001);
- reasons related to the **lack of transparency** of certain foreign jurisdictions (e.g. off-shore countries) where investors may decide to set up businesses in order to conceal their beneficial ownership.

Moreover, the share of owners of a certain nationality in a country may depend on opportunities related to **geographical proximity** (e.g. shareholders from Belgium may be more frequent in the Netherlands than in Portugal because the former is closer) or to **cultural links** or common historical roots (e.g. crown dependencies or former colonies).

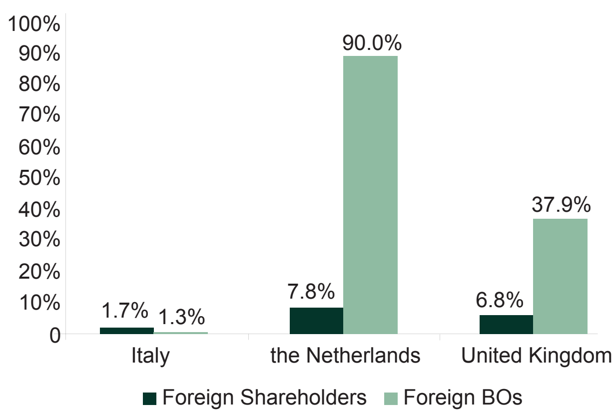
Foreign shareholders and BOs in the three IARM countries

These factors could potentially help to explain the differences among the three countries in terms of foreign ownership (see chart below). The Netherlands and the UK show much higher figures than Italy regarding both **foreign shareholders and foreign BOs**. While only 1.7% of shareholders and 1.3% of BOs of Italian companies are foreign persons, the share of foreign shareholders is 6.8% in the UK and 7.8% in the Netherlands, and the difference in terms of BOs is even wider (37.9% in the UK and 90.0% in the Netherlands).[107]

The higher values in the Netherlands and UK may be related to the – well acknowledged – **lower costs and bureaucratic obstacles** in starting a business in those countries compared with Italy (The World Bank, 2017)[108]. Moreover, the presence of international financial hubs (in particular the City of London in the UK) and of corporate tax incentives (especially in the Netherlands - Tromp, van Rossum, Buehn, & van Kommer, 2013) may help explain the gap between the three countries. The higher ranking of the Netherlands and the UK in terms of **FSS – Financial Secrecy Score of the Financial Secrecy Index** – could also suggest that these countries may be preferred because of the lower transparency – but this issue will be explored further below.

Figure 62 - % of Foreign shareholders and BOs at country level (Italy, the Netherlands and UK)

Foreign shareholders: Italy (N=44,971), the Netherlands (N=35,953), UK (N=73,222);
Foreign BOs: Italy (N=26,500), the Netherlands (N=24,603), UK (N=99,514);



Source: Transcrime – UCSC elaboration

107. Data in the Netherlands may be affected by the low number of companies for which information on beneficial ownership is available (see Chapter 3 for details).

108. See e.g. the average time required to start a business as recorded by World Bank here: http://data.worldbank.org/indicator/IC.REG.DURS.FE?end=2016&start=2016&view=map&year_high_desc=-false

As regards the **nationalities of shareholders**, US American, German and French are most frequent in all the three IARM countries. Here the possible explanation may be related to the higher volume of trade and financial exchanges between these jurisdictions, and to cultural and geographical proximity. Some other jurisdictions – **Switzerland, Luxembourg, Cyprus, the Netherlands and Curaçao** – could be also related to **tax optimisation (and tax avoidance)** reasons (EURODAD, 2015; Tax Justice Network, 2015a). This is even more apparent when the nationality of *shareholder-legal persons* is analysed, a situation in which jurisdictions characterised by lower tax rates and laxer transparency regimes are even more frequent (see Chapters 2, 3 and 4).

Table 58 – Top 10 nationalities of foreign shareholders (% of total foreign shareholders)

Italy		The Netherlands		United Kingdom	
Shareholders from	**% on tot.**	**Shareholders from**	**% on tot.**	**Shareholders from**	**% on tot.**
Switzerland	11.4%	United States	20.7%	United States	24.3%
Germany	10.2%	United Kingdom	10.8%	Germany	8.8%
United Kingdom	9.5%	Belgium	8.9%	The Netherlands	6.4%
United States	7.8%	Germany	8.8%	Ireland	5.6%
France	7.6%	Luxembourg	6.4%	France	5.3%
Luxembourg	7.5%	France	5.0%	Switzerland	4.1%
The Netherlands	4.9%	Curaçao	4.3%	Australia	3.2%
Spain	4.0%	Switzerland	3.4%	Italy	3.2%
China	3.6%	Italy	2.8%	Luxemburg	3.0%
Romania	3.5%	Cyprus	2.2%	Sweden	2.1%

Source: Transcrime – UCSC elaboration

Table 59 – Top 10 nationalities of foreign beneficial owners (% of total foreign BOs)

Italy		The Netherlands		United Kingdom	
BOs from	**% on tot.**	**BOs from**	**% on tot.**	**BOs from**	**% on tot.**
Spain	21.7%	Spain	28.7%	Spain	28.7%
Germany	15.8%	Germany	24.3%	Italy	21.4%
Switzerland	13.0%	Italy	11.0%	Germany	12.5%
China	4.9%	Switzerland	7.8%	United States	6.0%
Romania	4.4%	United Kingdom	4.0%	Switzerland	4.0%
United Kingdom	3.9%	Austria	3.0%	Saudi Arabia	3.5%
France	3.6%	Belgium	2.7%	South Africa	2.4%
Austria	2.6%	France	2.6%	Ireland	2.1%
Albania	2.4%	Denmark	2.1%	The Netherlands	2.0%
United States	2.4%	United States	1.9%	France	1.8%

Source: Transcrime – UCSC elaboration

As regards foreign beneficial owners, Spanish, German and Italian BOs are among the top 4 jurisdictions in the three countries. US American and French BOs also rank high. Other nationalities may be affected by the **presence of migrants' communities** (e.g. the Romanian and Chinese communities in Italy or the Irish and South African ones in the UK).

Spanish are the most frequent foreign BOs (21.7% in Italy, 28.7% in the Netherlands and 28.7% in the UK). This result is surprising, considering the relatively small Spanish communities in those three countries and the limited role played by Spain in terms of foreign trade and investments (with the exception of some business sectors such as energy or finance). In-depth investigation of this figure in Italy (see Chapter 2) reveals that Spanish BOs are very present in some southern provinces and in some sectors (such as R92 – Gambling) which have often recurred in investigations against Camorra and 'Ndrangheta OC. This anomaly may be then related to potential ML risks, but should deserve further research and investigation

Ownership links to risky jurisdictions

However, as mentioned in previous chapters, not all foreign nationalities encompass the same level of ML risk. The transparency (or opacity) widely varies across countries, and a variety of jurisdictions – **tax havens, off-shore areas**, etc. – exist which use financial and corporate secrecy to attract legitimate and illicit financial flows (Tavares, 2013; Tax Justice Network, 2015a).

In order to understand, in each of the three countries, the level of connections with risky jurisdictions, IARM has developed a measure of riskiness combining BvD data with Tax Justice Network (TJN) indicators.

How IARM measures the level of business ownership connections with risky jurisdictions

The opacity of foreign shareholders and BOs' jurisdictions is measured through an index produced by the Tax Justice Network: the Secrecy Score (called FSS in this report) of the FSI - Financial Secrecy Index (FSI) (Tax Justice Network, 2015a).

The FSS is issued every 2 years. It is a composite indicator which evaluates different dimensions of secrecy/opacity in the legislation, banking and financial sector. In particular:

- the level of banking secrecy;
- the access to beneficial ownership information;
- the transparency of corporate information;
- the efficiency of tax and financial regulation;
- the compliance with international standards (e.g. FATF Recommendations);
- the level of international cooperation

All these dimensions are combined into a score ranging from 30.87 to 86.64. The FSS is preferred to other measures of risky jurisdictions (e.g. international or national blacklists) because of the independency and transparency of the methodology, as already acknowledged by previous academic and institutional studies (see e.g. Cassetta et al., 2014; Gara & De Franceschis, 2015; Riccardi, Milani, et al., 2016).

Under the IARM framework, the share of each nationality among shareholders and BOs is multiplied by the relevant FSS value in each area or sector. In detail, given:

x = number of shareholders or BOs
j = nationality of shareholders or BOs
i = country or region or NACE sector of registration of companies
FSS = Secrecy Score of the FSI

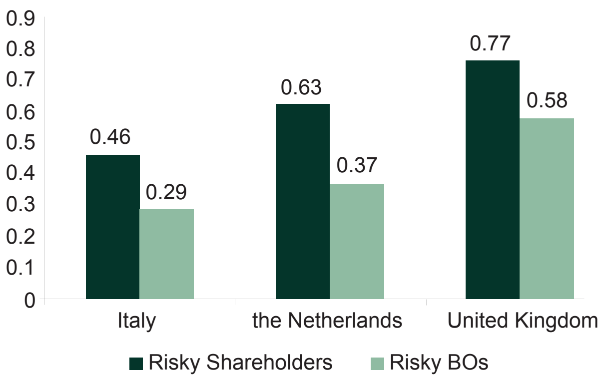
$$RISKY\ SHAREHOLDERS_i = \sum_{j=1}^{j}{}_i \left[\frac{x_{ij}}{\left(\sum_i^J x_j\right)_i} \times FSS_j \right]$$

For shareholders and BOs resident in the country, their FSS is set equivalent to zero. The assumption is that for an investigator is easier to check natural or legal person resident in the country, while it is more difficult to do so with non-domestic shareholders or BOs.

Thus, the final ranges from 0 (only domestic shareholders or BOs) to 86.6 (highest risk – all shareholders or BOs originated from the country with the highest FSS score – i.e. Vanuatu).

The risk scores calculated at the country level are presented in the figure below. Although all the three countries have relatively low risk scores, slight differences are apparent. In particular, **Italy seems to record a lower volume of business ownership connections** with risky jurisdictions when considering both shareholders (0.46 vs. 0.63 in the UK and 0.77 in the Netherlands) and BOs (0.29 in Italy vs. 0.37 in the Netherlands and 0.58 in the UK).

Figure 63 – Ownership risk score indicators at country level (Italy, the Netherlands, UK)



Source: Transcrime – UCSC elaboration

The higher "opacity" for the UK and the Netherlands may depend on several factors, including:

- The **higher percentage of foreign shareholders** and BOs in both the UK and the Netherlands[109]
- The more favourable **corporate tax regime** with respect to Italy, which in turn may attract a **higher number of multinational companies** with shareholders and BOs with, on average, a higher FSS

Indeed, UK is facing some issues regarding the presence of shareholders from tax havens, in particular after the **Panama Papers in 2016** revealed that UK clients of the Mossack Fonseca firm were among the most active ones in terms of number of incorporations of offshore companies.[110] Also for this reason, the UK recently pushed forward the establishment of the open register for BOs as required by the Fourth AML EU directive (EC, 2015).[111] UK concerns regard in particular land and real estate properties owners: "*The Metropolitan Police this year revealed that British property purchases worth more than £180 million were being investigated as the likely proceeds of corruption — almost all bought through offshore companies*" (Grimwood, 2016) – see also Chapter 4 for further discussion on opacity of UK-based businesses.

The risk scores are also calculated at sub-national area (in Italy and the UK) and business sector level. They are presented in each country-specific chapter (see Chapters 2, 3 and 4). Here, the score at business sector level is compared. The first table below reports the 'pure' score, i.e. not weighted by average company size, while the second table presents the score after weighting by average company size.[112]

109. see above: given the fact that the FSS of the country of company registration is posed as 0, the score overestimates the countries with a higher number of foreign shareholders
110. https://panamapapers.icij.org/graphs/
111. https://beta.companieshouse.gov.uk/
112. For the development of the indicator at sub-national area level and business sector level, the final score is eventually weighted by a proxy of average company size (specifically, the average total assets) in order to control for the presence of multinational firms within the business sector or area and then to identify actual anomalies (see Chapter 2, 3 and 4 and Annex for details).

Table 60 – Level of connections with risky jurisdictions by sector in Italy, the Netherlands and UK
NACE Sections excluding T and U. Section O excluded in the Italian analysis.
Standardised on 0-100 scale. 100 = highest risk

	Italy		The Netherlands		United Kingdom	
Business sectors – NACE Section	**Risky SH**	**Risky BOs**	**Risky SH**	**Risky BOs**	**Risky SH**	**Risky BOs**
A - Agriculture	0.0	0.0	0.1	0.2	1.8	0.5
B - Mining	35.7	6.3	100.0	100.0	100.0	39.1
C - Manufacturing	25.1	15.8	14.1	16.2	26.6	20.0
D - Energy	100.0	100.0	12.6	5.1	35.6	100.0
E - Water & waste	5.9	9.8	4.9	6.1	16.2	7.4
F - Construction	7.2	5.5	0.8	0.7	2.1	1.8
G - Wholesale & retail	13.1	9.4	4.6	15.8	9.5	14.2
H - Transport	48.7	10.6	5.9	13.5	12.4	10.2
I - Hotels & bars	9.2	8.6	0.5	9.3	2.5	8.8
J - ICT	25.9	11.0	5.2	2.7	13.1	17.3
K - Finance	32.3	10.0	9.3	7.6	40.9	18.7
L - Real estate	19.7	9.3	4.4	8.2	3.9	20.3
M - Professional activities	27.7	17.9	2.1	2.4	10.6	16.0
N - Support services	17.3	12.3	3.7	6.0	13.1	16.8
O - Public Administration	n.a.	n.a.	0.1	0.0	0.0	0.0
P - Education	0.1	7.0	0.1	0.3	0.0	0.3
Q - Health & social work	0.0	5.9	0.1	0.2	0.3	0.6
R - Entertainment	0.1	17.8	0.1	0.6	3.0	1.7
S - Other services	0.0	0.7	0.0	0.2	3.0	2.5

Source: Transcrime – UCSC elaboration

- In **Italy**, section D (Energy) scores highest for both indicators of risky shareholders and risky BOs. Regarding risky shareholders, also sections H (Transport), B (Mining) and K (Finance) are very high, while section R (Entertainment), which includes gambling activities, presents a high score as regards BOs.
- In the **Netherlands**, section B (Mining) shows the highest opacity among business sectors, followed by Section C (Manufacturing) to a much lower extent.
- In the **United Kingdom**, section B (Mining) and D (Energy) rank highest. Section K (Finance) presents a high score in terms of risky shareholders, while section L (Real estate) scores high in terms of risky BOs.

As mentioned, most of the sectors ranking high are characterised by a larger number of big and **multinational companies** (e.g. in the energy and mining sectors, which also include oil and gas, and also in some manufacturing divisions, such as pharmaceuticals) which more likely make use of holding companies set in tax-favourable and offshore jurisdictions. In order to see anomalies besides the presence of multinationals, the second table presents the scores after weighting by company size. The results change significantly.

Table 61 – Level of connections with risky jurisdictions by sector in Italy, the Netherlands and UK
Weighted by company size (average total assets). NACE Sections excluding T and U.
Section O excluded in the Italian analysis. Standardised on 0-100 scale. 100 = highest risk

	Italy		The Netherlands		United Kingdom	
Business sectors – NACE Section	**Risky SH**	**Risky BOs**	**Risky SH**	**Risky BOs**	**Risky SH**	**Risky BOs**
A - Agriculture	32.2	20.1	22.9	1.7	100.0	26.1
B - Mining	12.3	0.0	8.6	0.7	14.2	3.6
C - Manufacturing	17.1	10.9	39.0	3.1	63.5	31.3
D - Energy	1.2	0.7	7.6	0.2	6.5	15.1
E - Water & waste	0.0	0.2	34.4	3.0	19.6	6.0
F - Construction	31.9	25.7	24.4	1.3	26.1	12.1
G - Wholesale & retail	42.0	32.9	70.9	16.6	86.8	77.5
H - Transport	4.9	3.1	61.3	9.7	49.4	26.1
I - Hotels & bars	100.0	100.0	86.9	100.0	67.3	100.0
J - ICT	32.5	14.5	100.0	3.6	67.7	55.6
K - Finance	9.8	1.2	10.3	0.6	0.0	0.0
L - Real estate	9.2	3.1	22.4	2.9	29.8	75.1
M - Professional activities	34.4	24.4	46.8	3.6	13.7	13.7
N - Support services	43.1	33.9	76.6	8.4	20.8	17.3
O - Public Administration			0.0	0.0	3.7	1.4
P - Education	52.3	45.0	58.1	6.9	20.2	9.3
Q - Health & social work	5.3	7.0	27.8	1.8	69.7	32.1
R - Entertainment	24.7	51.6	84.7	17.2	72.7	27.1
S - Other services	45.6	37.4	29.9	6.0	40.9	19.7

Source: Transcrime – UCSC elaboration

Now at the top are sector I (**Bars, restaurants, hotels**), and other NACE sections such as R (**Entertainment, gambling, gaming**), J (ICT and media) and also G (Wholesale and retail trade) much emerge. In the UK, also A (Agriculture) now ranks high, while to be noted is that **Section L (Real estate agencies)** remains very high in terms of BOs risk both when weighting and when not weighting by company size: this result seems to confirm the **concerns about investments from opaque and 'risky' jurisdictions in the UK property market** (see Chapter 4).

5.3 Research and policy implications

Thanks to the access to BvD data and to the development of an innovative set of proxies, IARM has conducted an **exploratory analysis** of the degree of opacity of business ownership in Italy, the Netherlands and the UK. The exploration is only the first attempt to investigate an increasingly crucial – but under-researched and extremely complex – topic: how European companies are controlled, by whom and for which purpose. The findings are very informative, but at the same time they require further analysis (together with an improvement of data quality).

Italian companies exhibit **more direct** control patterns. **BO distance** is lower than in the UK and the Netherlands. The volume of connections with risky jurisdictions (such as off-shore countries) is also more limited. However, these figures vary greatly according to the area and sector considered. After controlling by company size, sectors like I (Bars, restaurants and hotels), S (Personal service activities) and R (Entertainment) emerge promptly.

The **UK and the Netherlands** behave in a similar manner. They are both very open economies, attracting high volumes of FDI and multinational companies, also thanks to the efficient incorporation systems, financial hubs and favourable tax regimes. However, this also increases the riskiness **in terms of business ownership complexity** (with higher BO distance, especially in some areas such as UK Crown dependencies) and connections with off-shore companies.

At business sector level, the results are consistent across the three countries. Sections **B (Mining), D (Energy), E (Water and waste), K (Finance)** are characterised by higher complexity and opacity. But after controlling by company size, in order to offset the effect of multinationals' presence, section **I (Hotels and bars), G (Wholesale and retail) and R (Entertainment) emerge. In the UK, also L (Real estate)** emerges, highlighting the risk that individuals from opaque jurisdictions are involved in the UK property market. Another anomaly difficult to interpret is the high number of **Spanish beneficial owners** – the most frequent foreign BO nationality in all the three IARM countries.

All these results are only the beginning – further investigation is needed, and more research is necessary on how to treat these data and how to measure the complexity and opacity of business ownership. Undoubtedly, the results of this exploratory analysis go well beyond the perimeter of **AML policies**, and are of interest also to EU policy-makers dealing with **taxation, industrial planning, consumers' markets and international trade**. The extension of this analysis to the other EU countries would be very helpful for improving our knowledge on European business ownership.

Conclusions

This report presented the findings of **project IARM** (*www.transcrime.it/iarm*), co-funded by **European Commission, DG Home Affairs**.

IARM consortium

IARM was carried out by an international consortium including, as research partners:

- the **Università Cattolica Sacro Cuore – Transcrime** (Italy – IARM coordinator)
- the **Vrije Universiteit Amsterdam** (the Netherlands)
- the Department of Criminology of the **University of Leicester** (United Kingdom)

and as associate partners the Italian Ministry for the Economy and Finance (Italy), UIF - the Italian Financial Intelligence Unit within the Bank of Italy (Italy), the Dutch Ministry of Finance (the Netherlands), the Dutch Ministry of Security and Justice (the Netherlands) and the NPCC – National Police Chiefs' Council (United Kingdom).[113] Associate partners provided input and feedback but are not responsible for what is written in this report.

IARM output

IARM developed an exploratory methodology to assess the risk of money laundering (ML) and in particular a composite indicator of money laundering risk:

- At **geographic area** level
- At **business sector** level

The methodology was tested in three pilot countries:

- **Italy** (see chapter 2), where a ML risk score was developed for the 110 provinces and 77 business sectors (NACE divisions)
- **the Netherlands** (chapter 3), where a ML risk score was developed for 83 business sectors (NACE divisions)
- the **United Kingdom** (chapter 4), where a ML risk score was calculated for the 43 police force areas of England & Wales.

Moreover, IARM carried out a pioneering analysis of the shareholders and beneficial owners of Italian, Dutch and UK companies to explore their exposure to off-shore countries and other 'risky' jurisdictions (chapter 5).

IARM strengths and weaknesses

Building on FATF guidelines and on previous NRAs and SNRA, IARM developed a methodology which follows various steps:

- the identification – in each of the three covered countries – of **ML risk factors (*threats and vulnerabilities*** according to FATF taxonomy)
- their operationalisation into a set of variables to allow measurement;
- their combination in a **single composite indicator** of ML risk, at both area and business sector level;
- the **validation of the final indicator** through sensitivity analysis and a range of tests.

The analysis was supported by a comprehensive **review of the literature** (e.g. FATF reports, FIU and LEA reports, judiciary evidence, academic literature) and by a number of **interviews with experts** (e.g. policy-makers, public officers, industry representatives at national and EU level, researchers).

The IARM methodology relies (mostly) on **public data** and it is designed so it can be replicated in other countries and contexts. With respect to existing NRAs, it stresses the **quantitative approach** and provides some important added values, like the higher disaggregation detail (e.g. sub-national perspective vs. national perspective of most of current NRAs) and the wider coverage of business sectors.

113. Support has been provided also by UK Home Office. See Acknowledgements section for the full list of people and institutions that have supported the project.

In particular the IARM methodology is affected by **data quality and availability** – it works better in contexts characterised by richer set of information, while it may underestimate those risk factors for which data are still lacking.

However, it is not intended to replace existing NRA but only to complement them. A comprehensive understanding of ML risks could be obtained only c**ombining a quantitative analysis** – like the one conducted by IARM – with a **qualitative perspective** which could take into account of experts' insights into emerging ML trends.

Table 62 - IARM methodological approach – Strenghts and weaknesses

Strenghts	Weaknesses
• Complex phenomenon condensed into a single measure of risk • Sub-national perspective (vs. NRAs' national perspective) • All business sectors covered (vs. NRAs' coverage of regulated sectors only) • Transparent and replicable methodology • Easily applicable in the everyday work of AML practitioners (e.g. in CDD by obliged entities)	• Suffers from lack of data on certain risk factors and emerging trends (e.g. virtual currencies, NPMs) • No coverage of risk factors at national level (e.g. weaknesses in AML legislation) • No coverage of ML consequences • Focus on ML (and not on TF)

Policy and research implications

The indicators of ML risk developed by IARM could support the **operational activity** of both public agencies and private entities, for example:

- **policy-makers**, to better allocate AML resources and measures across the areas and sectors based on their ML risk level;
- **investigative agencies** (e.g. LEAs and FIUs), to identify the areas and sectors on which to strengthen monitoring and investigation;
- **obliged entities** (e.g. banks, professionals, etc.), to enrich the set of indicators and red-flags to be used in AML customer due diligence (CDD).

IARM also provided a first contribution to the understanding of if and how the **ownership of legitimate companies** – in Italy, the Netherlands and UK - is related to money laundering risks. **Anomalies in terms of businesses' opacity and complexity could be identified** in relation to specific geographic areas, business sectors and nationalities of shareholders and beneficial owners, which would deserve further investigation and research – not only for AML but also for **tax evasion** purposes.

Another concern is the relation between ML and **cash-intensive businesses and regions**: data on cash is generally scarce, but when it is available, it indicates a correlation between cash-intensiveness and various illicit activities (like underground economy, tax evasion and organised crime).

However, it must be noted that IARM is only a **first step** towards a more robust assessment of ML risks. It follows an exploratory methodology which would much benefit from enhanced **data availability and quality**. In particular, it would be necessary to improve the collection of statistics:

- on important ML threats such as **tax crimes and fraud**, for which data are scanty in most EU countries, especially at business sector level;
- on important ML vulnerabilities such as **cash use**, for which statistics (e.g. on payments) are available in most EU countries only at the national level but not across regions and sectors;
- on the **ownership structure** of European businesses, for which data are only available through private data providers, and still virtually impossible to obtain in harmonised format across EU MS public business registers.

- on **suspicious transaction reports/suspicious activity reports (STRs/SARs)** which could be very rich sources of information also for research purposes, but are only partially exploited for this reason.[114]

In order to improve the quality and availability of data in a cross-sectorial field such as AML, it is suggested that European agencies better **cooperate to exchange information**, and that ad-hoc initiatives (such as more capillary surveys on cash use across countries and sectors) are taken. In addition, **public-private partnerships** should be strengthened, with a wider data sharing by the industry (e.g. from banks and other AML obliged entities).

It is also suggested that the IARM approach could be **replicated in other European countries** to test its validity and refine the methodology. A more in-depth analysis of the **ownership structure** of European businesses should be carried out, to better understand the drivers behind cross-border ownership links and to identify anomalies in shareholding and beneficial ownership schemes.

The benefits of such interventions would go much beyond the AML field, reinforcing also the fight against **terrorist financing, tax evasion** and **corruption** and improving the efficiency and security of the EU internal market.

114. Exceptions exist. See for example the in-depth analyis provided by the UIF – Italian Financial Intelligence Unit (within the Bank of Italy) in its Quaderni dell'Antiriciclaggio, and in particular the Quaderno n. 4, November 2015 (https://uif.bancaditalia.it/pubblicazioni/quaderni/2015/quaderni-4-2015/index.html)

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