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MAGIC MIRROR IN MY HAND…HOW TRADE MIRROR STATISTICS CAN HELP US DETECT ILLEGAL FINANCIAL FLOWS

by Mario Gara*, Michele Giammatteo* and Enrico Tosti**

Abstract

Criminals worldwide typically use misreporting tricks of different sorts to exploit the transfer of goods between different countries for money laundering purposes. The main international anti-money laundering organisations started paying attention to this phenomenon, known as trade-based money laundering, or TBML, a long time ago, but the absence of suitable analytical tools has reportedly impeded preventive action. Nonetheless, the literature has consistently shown that the analysis of discrepancies in mirrored bilateral trade data could provide some help. Based on previous studies, this work builds a model factoring in the main structural determinants of discrepancies between mirrored data concerning Italy's external trade in the period 2010-13, considered at a highly detailed (6-digit) level of goods classification for each partner country. Point estimates of freight costs are used to net the cif-fob discrepancy. The regression estimates are then used to compute TBML risk indicators at country and at (4-digit) product level. Based on these indicators, rankings of countries and product lines can be compiled and used to detect potential illegal commercial transactions.

JEL Classification: E26, F14, K42.
Keywords: Money laundering, illicit trade flows, mirror statistics.

Contents

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1. Introduction[1]

An importer in Country A purchases goods from an exporter in Country B and requires that the goods be delivered to its branch in Country C. The importer settles the invoice of the exporter by a wire transfer. The importer then invoices its branch for a significantly higher value, including a wide range of inflated administrative costs, which in fact are added so as to allow for the transfer of funds of illegal origin. The branch settles the inflated invoice by depositing funds into its parent's bank account.[2]

The scheme which has just been described, taken from a real life case, illustrates how the physical movement of goods through the trade system can be exploited by criminals as an efficient channel for disguising the unlawful nature of the proceeds of their activities and integrating them into the legal economy. Indeed, influential international organisations competent in the field of money laundering, such as the Financial Action Task Force (or FATF), have long started looking at this phenomenon, typically referred to as Trade-Based Money Laundering (TBML henceforth), since it has reportedly garnered relevance as a conduit of cross-border flow of ill-gotten funds, alongside the use of the financial system and the physical movement of cash.

Accounting tricks offer a wide range of techniques granting wide enough a room for manoeuvre for producing international financial flows bereft of inherent economic rationale but on paper. As in the case illustrated above, under- or over-invoicing (depending on the desirable direction of the funds to be transferred) or false invoicing altogether[3] can be usefully deployed in order to create artificially inflated payments outgoing from a goods-importing country or to curb otherwise much higher incoming transfers accruing to an exporting jurisdiction.

The most obvious underlying purpose of shenanigans of this kind are possibly connected to what can be defined, with an understatement, as tax optimization policies, aiming at lowering the tax burden of a company in a high-tax rate country and raising it in tax-payer friendlier jurisdictions. This type of flows can be taken to be illegal only to the point that the underlying tax conducts amount to a criminal behaviour, which is not necessarily the case in all jurisdictions. Alternatively, the financial wedge between the actual value of the goods being exchanged and the corresponding movement of funds may be connected to the proceeds from the supply of illegal goods and services (such as drugs, weapons, human beings trafficking and kickbacks) or to create cash reserves that can be consequently further transferred with no legal obstacles and put to different uses.

Possibly such misalignment between what is owed and what is actually paid in connection with a given exchange of goods can be reflected in national trade statistics since either accounting or custom documentation presented in different countries may not necessarily coincide. That could be visible by comparing mirrored bilateral trade data (so-called mirror statistics) measuring the exchange of goods at some level of details between a country and each commercial partner. Thus, mirrors, in trade statistics as in fairy tales, may turn out to possess extremely powerful properties in detecting menaces of some sort.

Alongside purposeful misevaluation of goods, another possible source of discrepancies

[1] The views and the opinions expressed in this paper are those of the authors and do not necessarily represent those of the institutions they are affiliated with. We wish to thank for their useful comments Giuseppe De Feo, Silvia Fabiani, Domenico J. Marchetti, Claudio Pauselli, an anonymous referee, seminar participants at UIF, 2016 SIDE-ISLE Conference in Turin, Eurostat meeting on Illegal Economic Activities in National Accounts and Balance of Payments (March, 2017) and the 2017 UIF-Bocconi Workshop "Quantitative methods and the fight against economic crime".

[2] The case is taken from FATF (2006).

[3] False invoicing may be arguably applied much more easily to intangible products, such as services, but less so to physical goods that can be weighted, counted and measured some way or another. Indeed, an analysis of the service sector is indicated as one of the potential further avenues of our research in the concluding sections of the paper.

between two countries' mirror statistics is misreporting, which can either refer to the type of goods being exchanged or their country of origin/destination. Quite tellingly, in the case illustrated above the circumstance whereby the country the goods are shipped to differ from the country where the buyer resides may potentially lead to the misalignment of the recorded partner country for this particular trade. Misalignment due to incorrect reporting can be due to the inefficient reporting system of the countries involved in a trade flow (more likely if either is a developing country) or to different goods classification criteria (which is less frequent when countries are regular commercial partners or are parties in multilateral trade treaties). Alternatively, misreporting can also be deliberate, which may entail the same opaque underlying motivations attached to misevaluation.

Misreporting in all its shapes may pursue a wide array of objectives, in addition to those which have just been mentioned: an importer may declare the shipment of a different type of goods from the one actually delivered in order to pay lower tariffs; an exporter may indicate an incorrect country of residence of the commercial partner so as to by-pass commercial embargoes of some kind. The purpose of this work is that of analysing only those cases in which reporting hoaxes can be used as a conduit for ill-gotten financial resources as opposed to those instances in which invoicing or reporting tinkering pursue other illegal goals.

Based on previous works in this field, we estimate a linear mixed model aiming at identifying the main determinants of mirror statistics discrepancies. The latter are specified, with reference to Italian trade flows for the 2010-2013 period, at a level of 6-digit classification for each partner country. Explanatory variables include those accounting for inefficiencies in the reporting system in the partner country (which is often linked to the level of economic development) and possible misalignments of product classification (due to the lack of trade agreements or to infrequent trade flows).

Our work improves with respect to the existing literature in three main directions. Firstly, import and export values are adjusted for *cif/fob* discrepancies with point data based on the Bank of Italy's freight costs survey, instead of using fixed correction coefficients (typically a 10% mark-up). Secondly, we apply a random effect econometric model that, using an extremely detailed goods classification (6-digit) and several country-level characteristics accounting for structural determinants of discrepancies, allows us to isolate the effects of factors possibly related to illegal financial flows and money laundering. Thirdly, we use the results of our model to define country-product indicators of TBML risk that authorities and operators in the field may apply for the detection of potential money laundering commercial transactions.

The study is structured as follows. Section 2 presents the research question and the related relevant literature; Section 3 describes the overall conceptual framework and the data used in the analysis. Section 4 sets out the econometric model and the empirical results obtained. Section 5 is devoted to the computation of our TBML risk indicators, which are then used to build separate rankings for (i) product-country pairs, (ii) countries and (iii) product lines according to the respective riskiness; in addition, we develop a correlation analysis between the indicators and some synthetic measures of country-specific risks associated to criminal activities. Section 6 contains some brief concluding remarks and further research proposals.

2. Research question and literature review

Both academicians and practitioners seem to agree in viewing international trade as a potential realm for concealing financial flows of illegal origin that may significantly appeal to criminals.

On the one hand, the main actors on the international anti-money laundering stage, first of all the Financial Action Task Force (or FATF, the OECD-based international standard setter in the field), have increasingly devoted their efforts to analysing TBML and devising tools and techniques to detect and prevent it. In a 2006 typology report (FATF, 2006), TBML is defined as "*the process of disguising the proceeds of crime and moving value through the use of trade transactions in an attempt to legitimise their illicit origins*" which takes place "*through the misrepresentation of the price, quantity or quality of imports or exports"*. The analysis concludes that TBML "*represents an important channel of criminal activity and, given the growth of world trade, an increasingly important money laundering and terrorist financing vulnerability*", also as the result of the ever rising effectiveness of the counter-measures preventing other money laundering techniques.

In spite of the widespread awareness of the growing relevance of TBML, the Asia/Pacific Group on Money Laundering, a regional offshoots of FATF's, in 2012 acknowledged that "[a] *major obstacle in devising strategies to tackle TBML has been the lack of reliable statistics relating to it*" (APG, 2012).

In this regard, a long-standing strand of academic studies may come to the rescue. Indeed, several studies point at discrepancies and inconsistencies in trade statistics as potentially revealing footprints of those illegal flows that are inter-mingled with official international trade.

Early adopters of this approach are Bhagwati (1981) and Pitt (1981), who rely on the hypothesis that not only do legal and illegal trade (broadly defined as including trade of licit goods traded in an irregular way) takes place hand in hand, but the latter requires that some of the former is actually registered so as to minimise the risk of detection. Hence, remnants of financial flows arising from illegal trade can be found between the cracks of official statistics.

Various approaches are put forward to separate the wheat from the chaff, the most promising of which relies on the pairwise comparative analysis of mirrored bilateral trade statistics of commercial partner countries. In theory, country *i*'s exports to country *j* should be equal to country *j*'s imports from country *i* in each sector they trade in. In practice, this is rarely the case: it is common, for instance, to encounter what are typically defined as *orphan imports* or *missing exports*, i.e. trade flows data in one direction that are not matched by the corresponding data in the opposite direction.

McDonald (1985) notes that in most studies the import-export discrepancy, net of insurance and freight costs, is assumed to reflect illegal trade. Likewise, Fisman and Wei (2009) argue that systematic misconduct by traders may partly explain the gap between mirrored exports and imports data.

Federico and Tena (1991) identify different causes that may underlie discrepancies of the kind, including what they call unavoidable factors (such as the *cif/fob* wedge), structural differences (for instance, those associated to a different reporting system between two partner countries), human errors (to be put down to custom officers or traders) and deliberate misreporting, the latter being the phenomenon that is closely related to illegal trade (see Table 1).

Different types of misreporting are classified in Hamanaka (2012), who distinguishes between commodity misclassification (when the kind of goods being exchanged are mistakenly stated) and direction misclassification (when it is the country of origin or of destination that is incorrectly reported). To these two instances, one has to add deliberate misinvoicing, which is a type of misreporting involving either the quantities exchanged or the price applied to the exchange (Bhagwati, 1981).

Most studies analysing mirror statistics disparities with the aim of explaining their determinants do not adopt a wholesale approach to the issue. Thus, just to mention a few, Carrère and Grigoriou (2014) mainly examine so called *orphan imports*, though they also build a model for explaining the intensity of *cif/fob* gap, taken as a gross indicator of discrepancies. Buehn and Eichler (2011) develop four different models so as to explain each and every occurrence that can be observed (import under-reporting, import over-reporting, export under-reporting and export over-reporting).

Table 1
Causes of discrepancies between mirror data

Factors	Causes	Change in Price and/or Quantity
Unavoidable factors	*Cif/fob* difference • freight cost • insurance cost	Price
Structural differences between two customs offices	Coverage • differences in rules of origin (especially in the cases of re-export) • processing zone • returned goods	Quantity
	Time lag	Quantity
	Exchange rate	Price
Deliberate misreporting by traders and errors committed by customs offices	False declaration of value by traders	Quantity and Price
	False declaration of origin by traders	Quantity
	Commodity misclassification by customs	Quantity
	Direction misclassification by customs	Quantity

Source: Hamanaka (2012)

In our approach, we follow Nitsch (2011) in that we focus our analysis on the two instances which can be connected to the unrecorded movement of funds outside a country (capital flight), that is import over-reporting and export under-reporting.

Most of the studies take a micro view of the main drivers that may underlie deliberate misreporting. De Boyrie *et al.* (2005) concentrate on potential price misreporting: holding discrepancies between international prices and prices applied in bilateral trade between Russia and the US in the early nineties as signals of illegal trade conducive to capital flight, they explain such discrepancies by adopting a portfolio approach, including interest and inflation rate differentials and exchange rate volatility as potential determinants. Patnaik *et al.* (2012) add to this lot political and economic stability and exchange rate volatility. Buehn and Eichler (2011), alongside tax rates, tariffs and the probability of detection, take also into account the existence of foreign currency black markets in the countries examined with the resulting misalignments between the official and the underground exchange rate as potential source of illicit profits. Our approach mimics that of Carrère and Grigoriou (2014) and Berger and Nitsch (2012) in that our model includes macro explanatory variables which are liable to underlie discrepancies in mirror statistics. One crucial difference is that we take a 'residual approach': by attempting to capture the structural (or physiological) components of the observed gaps, the share of the dependent variable that remains systematically unexplained by our model is taken as a proxy of the phenomenon being examined, that is deliberate trade misreporting[4].

Such an approach secures two advantages with respect to other studies. Firstly, any explanatory variable that may be included in the model so as to control for illegal conducts or aims turns out to explain it only to a very limited extent: for instance, both Carrère and Grigoriou (2014) and Berger and Nitsch (2012) use indicators of perceived corruption as explanatory variables, falling far short to account for all determinants of capital flight, which can also be motivated by the need to launder ill-gotten earnings or to pay for illegal goods and services. Since indicators that may plausibly be used as proxy for these drivers are difficult to find, leaving them unaccounted for and analysing the estimate residuals may be the best option to capture their

[4] In the literature on indicators of money laundering risks, the methodology – based on regression residuals – was first proposed by Cassetta *et al.* (2014) and Ardizzi *et al.* (2016).

effects.

Secondly, such approach serves extremely well the main purpose of our work. Our aim is not that of estimating the value of misreporting and the corresponding capital flight. Many authors have had several goes at this exercise, very few of them with useful results, so that hardly can one disagree with Nitsch (2016), who states bluntly that "*the quantitative results obtained from those exercises have no substantive meaning*".

Our main goal is different: we aim at building risk indicators that may be used to identify patterns of trade (at a country/sector level) that are more liable to conceal illegal traffics. In most studies mentioned above, such indicators are based on gross data, that is patterns emerging irrespective of the results of the econometric estimates, which are only used to identify the main determinants of mirror statistics gap. In our work, the indicators are explicitly built on the results we obtain from our model, more precisely, on the estimated random effects.

Our work improves on previous studies in another relevant methodological respect. We make use of the results of the sample survey on international merchandise transport, that the Bank of Italy has carried out since 1999 on a yearly basis, which estimates freight rates according to the structure of the reference market (Pastori *et al.,* 2014 and Bank of Italy, 2016). The survey provides point estimates for freight costs at an extremely detailed level of accuracy, enabling us to correct each observation for the proper *cif/fob* wedge with a very significant impact on the precision of our final estimates, instead of applying a 'one-size-fits-all' 10% correction factor, as it is used throughout the literature.[5]

3. Conceptual framework and data

3.1 Typology of misinvoicing and the construction of the model

There are a number of good reasons for firms to misreport data (invoice price or quantity, partner country, type of goods) with reference to an export-import transaction, such as tax avoidance, tariff evasion, transfer pricing, and avoidance of capital controls. The result of these reporting misconducts are misalignments in trade statistics, because different data may be provided to the various authorities in the various countries involved. If we consider the trade between Italy *vis-à-vis* any other partner country, four different discrepancies can therefore emerge:

1. **Under-reporting of Italy's exports** enables Italian exporters to shift a part of their taxable income out of the country, and possibly denominate it in a foreign currency.
2. **Over-reporting of Italy's exports** usually pursues the aim of illicitly earning subsidies and export tax credits (such as duty drawbacks, concessional rate on export finance, etc.), which are typically granted to high performing exporters; another rationale for export over-reporting is that it may be exploited so as to bring back illicit capitals detained outside the country.
3. The most relevant reason for **under-reporting Italy's imports** is the relatively high rate of import duties, since in this fashion the importer curbs the amount of duties she is liable to pay.
4. Capital flight may be the main factor underlying **over-reporting of Italy's imports**, as it allows the Italian importer to illicitly funnel capitals out of the country.

As the goal of our work is to analyse the possible ways of moving capital illegally abroad from Italy, we have focused our analysis on the hypotheses described under 1 and 4.

[5] As noted by Nitsch (2016), "[t]*his arbitrary assumption has a direct impact on the results since any difference in the observed cif-fob-ratio above or below a value of 1.1 is interpreted as overinvoicing or underinvoicing, respectively. The assumption is arbitrary since, in practice, cif-fob-ratios vary strongly, for various reasons [...]; the assumption of a fixed correction factor [...] seems to be a debatable oversimplification*".

The following Table 2 shows the key summary statistics for each of the four cases defined above on the whole sample of Italian trade transactions and, separately, for the sub-sample of observations used in the econometric application of Section 4. The observed distributions are highly skewed - with average values that overcome (in absolute terms) that of the medians - and characterised by top 5% of discrepancies exceeding 3.5 million dollars.

Table 2
Summary statistics
(2010-2013)

Type of discrepancies[a]	N	%	Mean	Median	p95[b]	p99[b]	CV
			Italian import discrepancies				
Negative	184,652	40.0	-2,410,859	-95,846	-5,534,031	-25,255,274	-29.2
Null	385	0.1	-	-	-	-	-
Positive	276,675	59.9	1,618,691	36,769	3,560,224	20,657,392	26.5
Total	461,712	100.0	5,807	2,648	1,784,382	12,490,377	9,559.8
			Italian export discrepancies				
Positive	608,497	61.2	878,616	46,331	2,795,269	13,327,250	13.7
Null	320	0.1	-	-	-	-	-
Negative	384,656	38.7	-1,094,798	-76,408	-3,413,910	-14,923,782	-20.2
Total	993,473	100.0	114,260	4,567	1,535,292	8,733,625	146.2
			Regression sample[c]				
Import discrepancies	*272,499*	*42.3*	*1,626,909*	*37,238*	*3,597,614*	*20,800,284*	*26.5*
Absolute *export discrepancies*	*371,426*	*57.7*	*1,117,586*	*78,848*	*3,509,760*	*-15,191,712*	*-20.1*
Total	*643,925*	*100.0*	*1,333,124*	*59,264*	*3,541,321*	*17,496,696*	*24.6*

[a] All country-6 digit observations for Italy in the COMTRADE database.
[b] For the negative discrepancies, the 5th and 1st percentiles of the partial distributions are symmetrically considered instead of the 95th and 99st, to allow consistency with the positive case.
[c] The number of observations is that of the sub-sample used in the Model 3 of Table 3, where some trade flows are excluded because of covariates missing values.
Source: authors' own calculations.

Noticeably, misreported trade flows of the kind we are scrutinising here may give rise to trade data asymmetries, but this is not necessarily the case, for instance if misinvoicing produces opposite effects that may cancel each other[6] or in the case of irregular transfer pricing conducts in intra-group transactions[7]. Therefore, trade asymmetries deriving from the comparison of bilateral data are to be considered as a lower bound of the size of phenomenon under analysis.

Regardless of the caveats, by examining trade discrepancies it may be possible to detect patterns which could hide financial flows of illegal origins. As we are interested in deliberate misreporting by traders, the way to proceed is to isolate the effect of the structural differences and the errors committed by customs offices. To do so, we have to find the right proxies.

[6] "[…] *if a shipment is underinvoiced in the exporting country to move capital unrecorded out of the country, and the shipment carries the same mispriced invoice in the importing country to evade import tariffs, no discrepancy in mirror trade statistics will occur*" (Nitsch, 2012, p.320).
[7] As reported by Yalta and Demir (2010): "*It should also be pointed out that combinations of incentives may actually be self-disguising in the sense that, if the partners recognize their mutual interests in such false reporting and collude in it, the data may look quite consistent (Yeats, 1990, p.2). This can be seen in terms of abusive transfer pricing by multinational corporations, who vary invoices to move profits and capital abroad (Kar and Cartwright-Smith, 2008)*".

3.2. The model: the dependent and explanatory variables

Based on the line of reasoning illustrated in the previous section, our dependent variable is built so as to include only those illegal conducts described under point 1 and 4 above , which we hold as channels allowing for funds to be illegally funneled abroad. Formally, we therefore only considers those instances in which:

(I) $\boldsymbol{EXP_{iITc} - IMP_{icIT} < 0}$ (under-reporting of Italian exports)

(II) $\boldsymbol{IMP_{iITc} - EXP_{icIT} > 0}$ (over-reporting of Italian imports)

with EXP_{ITc}=Italy's exports to country *c*, IMP_{cIT}=country *c*'s imports from Italy (*fob*), IMP_{ITc}=Italy's imports from country *c* (*fob*), EXP_{cIT}=country *c*'s exports to Italy, and i=product classification (6-digit[8]).

The discrepancies in mirror statistics are netted of the *cif/fob* distortions, taken in absolute value and then taken in logs.

We adopt what we dub as a 'residual approach'. In order to identify trade-based illicit cross-border transfer of funds, our model controls for the main structural (i.e., legal) determinants of mirror statistics gaps, as typically reported in literature (see Table 1[9]), and then take the estimate residuals (or a specific part thereof) as proxy measures of the illegal component of such discrepancies.

Our covariates include, first of all, GDP per capita of Italy's partner country, which is typically used as a proxy for the level of development of the country itself and hence of the reliability and effectiveness of its statistics reporting system. GDP is taken at 2005 constant dollar value and may be expected to have a negative relationship with trade statistics gaps.

Distance (*DIST*) is another factor impacting on the accuracy of trade statistics, since neighboring countries are also more likely to share commercial practices and reporting criteria; they also exchange data on a regular basis. Thus, one can expect that the larger the distance between Italy and a partner country, the wider the gaps observed in trade statistics.

Another proxy for trade regime commonalities which is customarily included in econometric models is countries' common membership in a regional trade agreement of some sort (RTA). Being members of the same economic or trade club generally involves also sharing reporting standards and customs practices, which in turn makes discrepancies in statistics less likely. In addition to a conventional binomial dummy (common membership vs. no common membership), we have also introduced a twist so as to account for the two-tier international cooperation regime applicable to Italy's trade partners, as many of them not only are signatories to the European Union treaties, but also feature a common currency (the euro). Hence, in an alternative specification of the model (see Table 3 below) the variable *EU* takes up three modalities: no RTA, EU member and Euro area member, with the last two expected to show a negative relationship with the dependent variable if set against the first.

A country's openness is another driver to be taken into account. As pointed out above, some pivotal contributions in the literature argue that in order to have illegal trade of some kind one has to have also some legal trade, since the latter help minimize the risk that the former is detected. Hence, the broader the trade relationships a country entertains worldwide relative to the size of its economy, the more chances there are that it attracts illegal trade flows alongside legal ones. Hence discrepancies can be expected to be positively correlated with any measure of a

[8] Products classification downloadable at https://unstats.un.org/unsd/tradekb/Knowledgebase/41.
[9] Table 1 also lists the time lag (differences in the timing of reporting or recording the same trade flows in different countries) among the potential determinants of discrepancies, but this should have a negligible relevance in our framework due to the use of annual data.

partner country's openness (*TROPEN*). To this scope, we consider the sum of merchandise exports and imports divided by the value of GDP.

Two additional covariates try to control for potential determinants of discrepancies that underlie some forms of deliberate misreporting which may not be associated to illegal cross-border trade flows of the kind we are interested in.

Firstly, we account for the tax regime in Italy's partner countries by taking into account the total tax rate on commercial profits (*TAX*[10]). This explanatory variable tries to address misreporting, such as under-invoicing of exports, which is fundamentally aimed at lowering the tax bill of the Italian exporter by exploiting a more favorable tax regime in partner countries. One would therefore expect that as the tax rate applied on average in the partner country rises, the incentive to misreport wanes accordingly. Arguably, conducts like false invoicing amount in most countries as predicate crimes for money laundering; introducing an explanatory variable that controls for such practices implies that, on the basis of our 'residual approach', our final indicators for TBML are cleansed of flows associated to tax evasion. Indeed, our focus is on specific types of illegal trade flows, those where the aim is that of creating concealed reserves in other countries for further illicit use or of paying for the supply of illegal goods or services. Hence our interest is to have final indicators which are net of effects which fall beyond the focus of our research.

The same line of reasoning applies to dodging custom duties, which is normally attained, for instance, by under-reporting imports. Custom tariffs[11] (*TARIFF*) applied by Italy's partner countries for each sector (6-digit level) is an additional covariate of the model controlling for this type of behaviour, which, albeit illegal, is not potentially conducive to outward money laundering-related trade flows.

The model is completed by introducing variables accounting for the scale of trade entertained by Italy in each 4-digit sector. Firstly, we include the mean of the value of trade between Italy and each partner country with reference to a broader (4-digit) product class than the one (6-digit) at which the dependent variable is defined, so as to allow for between-effects relative to different products. At the same time, the 6-digit deviation from such mean is also introduced in order to allow for product-specific within-effects. The reason for including this kind of 'size variables' is twofold: on the one hand, they allow to take into account scale effects due to the heterogeneous magnitude of trade between Italy and each partner country; on the other hand, possible endogeneity problems due to within-cluster heterogeneity of the same variables are explicitly controlled for.[12]

Finally, the model also features dummies for the broadest definition of product lines (2 digit) and for each year of analysis.

3.3. Data

Our first data source is the United Nations' COMTRADE database which includes information on trade flows expressed in thousands of current US dollars at the 6-digit level.[13] We took data concerning Italy's foreign trade from 2010 to 2013.[14] In a few cases some partner countries did not

[10] For some countries this information is available only for one or few years; in these cases (32 overall) missing values were replaced by the value of the closest period immediately preceding or following it.

[11] This variable is defined as the average between the Most Favored Nation (MFN) tariff and the Effectively Applied (AHS) tariff applied to each country-6 digit pair. Country-year missing values were set equal to a value just above zero (1E-09) in order to avoid indefinite log transformations.

[12] See Bell and Jones (2015) for a detailed discussion about endogeneity and the subsequent possible solutions in random effects models.

[13] http://comtrade.un.org/db/mr/daPubNoteDetail.aspx.

[14] The econometric application has been carried out on 152 countries. A first set of countries have been excluded from the analysis because not transmitting trade data with Italy during the whole reference period (this was the case of

report any trade with Italy in a whole year, making it all but impossible to compute any discrepancy; consequently the records for that country in that year were not included in our dataset.

For the conversion of imports from *cif* to *fob* values, we used data from the survey on Italy's international merchandise transport conducted by the Bank of Italy for balance of payments (BOP) purpose. In detail, merchandise transport items of Italy's balance of payment are calculated on the basis of external trade quantities multiplied by freight rates estimated interviewing about 200 transport operators; as a by-product, the difference between *cif* and *fob* values is derived, distinctly by country and product classification (Standard goods classification for transport statistics, NST2007; see Appendix and Bank of Italy, 2016).

As for gravity variables (distance and regional trade agreement), we used the CEPII database.[15]. The data source for GDP per capita and tax rate is the World Development Indicators published by the World Bank.[16]

Data on tariffs were taken from the World Bank's World Integrated Trade Solution (WITS) database, which contains information on "Most Favored Nation" and preferential tariff rates specific to pairs of countries and years, derived from the UNCTAD's Trade Analysis and Information System (TRAINS[17]). The tariff information is available at the 6-digit level.

4. Structural model and estimation results

4.1. The econometric model

The econometric analysis was carried out by implementing a linear mixed model. This kind of regression analysis enables to account for two different effects, fixed and random. In the former case, the corresponding estimates of intercepts and slopes refer to the population as a whole (as in ordinary regression), while in the latter random coefficients are allowed to vary across *clusters* of elementary units in order to capture unobserved heterogeneity at this aggregate level.

Mixed models can be thought of as *latent variable models* where a generic response variable is regressed on observed covariates and some other relevant not observed covariates are excluded, thus leading to unobserved heterogeneity. When the heterogeneity refers to groups of elementary units, intra-cluster dependence among the responses can typically arise.[18] In presence of a hierarchical structure of the data it is possible to introduce *cluster*-specific *effects* in order to account for the unobserved determinants and – if relevant for the research scope – to estimate the corresponding *random effects* in addition to the population-averaged fixed effects.

Consider the theoretical framework described in Section 3.2 and the following class of regressions. Elementary units refer to discrepancies at country-sector (6-digit) level; in particular,

American Samoa, Angola, Br. Virgin Islands, Chad, Cuba, Dem. People's Rep. of Korea, Dem. Rep. of the Congo, Djibouti, Equatorial Guinea, Eritrea, FS Micronesia, Faeroe Islands, Falkland Islands (Malvinas), Gabon, Gibraltar, Grenada, Guam, Guinea-Bissau, Haiti, Kiribati, Lao People's Dem. Rep., Liberia, Marshall Islands, Mayotte, N. Mariana Islands, Saint Lucia, San Marino, Seychelles, Sierra Leone, Somalia, Swaziland, Tajikistan, Tokelau, Tonga, Turkmenistan, Tuvalu, Uzbekistan). Others, although showing trade flows with Italy (at least in one year), were excluded because of missing dependent variable (Palau) or any independent covariate (Andorra, Aruba, Bangladesh, Bermuda, Cayman Islands, French Polynesia, Greenland, Libya, Macao, Montenegro, Myanmar, New Caledonia, Serbia, State of Palestine, Syria, Timor-Leste, Turks and Caicos Islands).

[15] http://www.cepii.fr/CEPII/en/bdd_modele/bdd.asp.

[16] http://data.worldbank.org/data-catalog/world-development-indicators.

[17] https://wits.worldbank.org/WITS/WITS/Restricted/Login.aspx, after registration.

[18] This typically leads to dependence between responses for units grouped in the same cluster and, as a consequence, misleading association estimate between dependent and independent variable.

we suggest the following basic specification of a *two-level random intercept model*:[19]

$$
\begin{aligned}
discrepancy_{ic} = {} & \beta_0 + \beta_1 tax_c + \beta_2 gdp_c + \beta_3 tropen_c + \beta_4 tariff_c + \beta_5 dist_c \\
& + \beta_6 EU/EMU_c \\
& + \beta_7 EXPORT_{ic} + \beta_8 (trade_{ic} - \overline{trade}_{jc}) + \beta_9 EXPORT_{ic} * (trade_{ic} - \overline{trade}_{jc}) \\
& + \beta_{10} \overline{trade}_{jc} + \beta_{11} EXPORT_{ic} * \overline{trade}_{jc} \\
& + sectoral\ (2\text{-}digit)\ dummies + year\ dummies \\
& + u_{jc} + \varepsilon_{ic} \qquad [1]
\end{aligned}
$$

where continuous variables (indicated in lowercase letters) have been transformed in their natural logarithms, and the dependent variable ($discrepancy$) is defined as the natural logarithm of the absolute discrepancies being observed, as defined by either equation (I) or equation (II) in pag. 11[20]. *EU* is a dummy variable equal to 1 if country *c* is a member of the European Union, 0 otherwise; *EMU* is a variable which can take three values: 0="country *c* is not EU member", 1="country *c* is EU member but not EMU member", 2="country *c* is both EU and EMU member". *EXPORT* is a dummy variable equal to 1 if the dependant variable refers to the case of export under-reporting (equation I), 0 if it refers to the case of import over-reporting (equation II). The third block of covariates includes the so-called 'size variables' mentioned above: $trade_{ic}$ is the value of trade between Italy and country *c* at 6-digit level: in the case of export under-reporting it is equal to the value of Italian exports to country *c* in sector *i* as measured by the average of the corresponding records in the Balance of Payments of the two countries[21]; in the case of import over-reporting, it is equal to the value of Italian imports from country *c* in sector *i,* measured likewise.[22] $\overline{Trade}_{jc}$ is the 4-digit average of $trade_{ic}$, with *j*=sector at 4-digit level. All variables (with the exception of distance and *EU/EMU* dummies) should have a subscript *t* (year), which is omitted for simplicity.

The regression coefficients β's represent the conditional (fixed) effects of the independent variables given the values of the random effects u_{jc}, which in turn can be interpreted as measuring 4 digit-country constant (unobserved) effects. As usual for random effects models, it is assumed that the clusters *j* are independent and that the total and group residuals are distributed as $\varepsilon_{ijc}|x_{ijc} \sim N(0, \sigma_\varepsilon^2)$, $u_{jc}|x_{ijc} \sim N(0, \sigma_u^2)$.

A fundamental assumption in random intercept models is that of independence between covariates and cluster residuals ($E[u_{jc}|x_{ijc}] = 0$). Generally referred to as endogeneity, a likely proof of correlation between higher-level residuals and covariates often leads to adopt *fixed-effects* strategy in order to obtain unbiased estimates through the elimination of the heterogeneity bias.[23] As pointed out by the literature (Mundlak, 1978; Skrondal and Rabe-Hesketh, 2004; Bell and Jones, 2015), this choice is neither the only option available nor the most effective, since a random effects approach – generally providing consistent and efficient estimates – has to be preferred if the following conditions hold: (a) unbalanced dataset are used, (b) group-invariant characteristics (not allowed to be explored through a fixed effect approach) are present, or crucially (c) the

[19] It is the simplest form of *linear mixed model.*

[20] More precisely, by using the notation introduced in Section 3.2, $discrepancy_{ic}$ is equal to $ln(|EXP_{iITc} - IMP_{icIT}|)$ in the case of export under-reporting, and to $ln(IMP_{iITc} - EXP_{icIT})$ in the case of import over-reporting. The dependant variable refers to export under-reporting for roughly 60% of the observations and to import over-reporting for the remaining 40%, as reported in Table 2.

[21] That is, $trade_{ic} = ln[(EXP_{iITc} + IMP_{icIT})/2]$.

[22] In this case, $trade_{ic} = ln[(IMP_{iITc} + EXP_{icIT})/2]$.

[23] In more general terms, fixed effect estimations provide only within-cluster effects simply removing all cluster variation.

research interest focuses in cluster specific effects. All this three criteria are fully met in our case, definitely supporting the choice of a random effects estimation[24].

4.2. Estimation results

Table 3 presents the baseline results. The first two columns correspond to simpler alternative specifications of our benchmark (Model 3) which differs from the other two because of the inclusion of the covariate on partner-country commercial taxes (*tax*) and the additional *EMU* category of 'Euro area membership'. The results highlight that the three models yield highly consistent estimates. The estimated coefficients of the continuous variables can be interpreted as elasticities, as both the control and dependent variables are expressed in logarithms.

All the estimated coefficients are significantly different from zero and with signs consistent with the theoretical hypotheses of Section 3.2. Higher total tax rate on commercial profits and GDP per capita of Italy's partner countries are associated to lower discrepancies in mirror trade statistics; the same sign is consistently observed for *EU/EMU* memberships, while the negative sign of the *EXPORT* dummy should be taken as evidence of the propensity of using import over-reporting as a preferred way to hide capital abroad with respect to export under-reporting. Moreover, partner country's openness, trade tariffs and geographical distance from Italy properly show positive relation with the response variable. In particular, each percentage increase of *TROPEN*, *TARIFFS* and *DIST* corresponds, on average, to a trade discrepancy increase of respectively 5.8%, 0.1% and 3.5% (benchmark model).

Finally, all the 'auxiliary' scale variables accounting for imports/exports size (both in country-4 digit means and corresponding country-6 digit deviations) show a positive and significant relation with our variable of interest. This allows us to control for an important factor underlying the dependent variable; the results show that mirror statistics discrepancies are positively correlated with the level and range of the observed trade values, in both the export under-reporting case and the import over-reporting one.

Obtaining coefficients estimate that match the theoretical hypothesis is obviously important to our end.[25] At the same time, it represents only a minimum requirement that our model should satisfy, since our aim is primarily that of obtaining as punctual as possible indicators of TBML risk. In particular, with regard to the (ex-post) random effects estimate, the *rho* coefficient shown in the last row of Table 3 indicates that 18% of the total model variability can be attached to the specific country-4 digit intercepts.[26] This signals the empirical relevance of this factor and allows us to rely on their distribution for the definition of the anomaly indicators presented in the next section.

[24] In particular, a) our database is characterised by product-country clusters including an extremely varying number of elementary units - in some cases 'singleton clusters' made of just one observation – that, unlike the case of fixed effect specification, are correctly estimated by random effects procedure, only requiring "the existence of a good number of clusters of size 2 or more" (Rabe-Hesketh and Skrondal, 2012); b) many of the model covariates are defined at country or product level; c) our final objective is defining TBML risk indicators as resulting from the model's random effects (or rather the empirical Bayes estimates thereof).

[25] In this regard, notice that the huge sample and random effects sizes allow us to obtain statistically efficient and consistent estimates. Moreover, the overall R^2 of 77% (only due to the fixed part of the model) allow us to claim an adequate goodness-of-fit of the model implemented.

[26] Likelihood-ratio tests, comparing the random effects model with ordinary regression, significantly reject the null hypothesis of random effects irrelevance.

Table 3
Random effects Estimates

	Model 1	**Model 2**	**Model 3**
tax		-0.038***	-0.046***
gdp	-0.011***	-0.014***	-0.017***
tropen	0.045***	0.056***	0.058***
tariff	0.001***	0.001***	0.001***
dist	0.019***	0.032***	0.035***
EU=1 (EU member)	-0.062***	-0.043***	-
EMU=1 (EU member but no EMU member)			-0.079***
EMU=2 (EU & EMU member)			-0.014*
EXPORT (=1 for export under-reporting)	-1.799***	-1.793***	-1.798***
$(trade_{ic} - \overline{trade}_{jc})$	0.826***	0.826***	0.826***
$(trade_{ic} - \overline{trade}_{jc})$* *EXPORT*	0.074***	0.074***	0.074***
$\overline{trade}_{jc}$	0.805***	0.805***	0.805***
$\overline{trade}_{jc}$* *EXPORT*	0.119***	0.119***	0.119***
2-digit sector dummies	Yes	Yes	Yes
year dummy 2010	0.051***	0.048***	0.048***
year dummy 2011	0.038***	0.036***	0.035***
year dummy 2012	0.007*	0.004	0.004
Constant	1.751***	1.807***	1.840***
N	646,511	643,925	643,925
N groups	82,100	81,142	81,142
R^2 *(overall)*	0.773	0.773	0.773
R^2 *(within)*	0.692	0.692	0.692
R^2 *(between)*	0.815	0.815	0.815
rho (variance share due to random effects: country-4 digit)	0.180	0.181	0.181

Benchmark: *not EU country*, *over-evaluation of Italian imports (EXPORT=0)*, *year 2013*.
Regression variable: *discrepancy*. All variables are in log, except *EU*, *EMU* and *EXPORT*.
Sample: 152 countries included in the analysis (see footnote 14 for details).
p-value: *** <0.01, ** <0.05, * <0.1.
Source: authors' own calculations.

5. Indicators of anomaly

5.1 Residual analysis of country-product effects

It was repeatedly stressed in the previous sections that our work's main purpose is the definition of indicators of TBML risk for operational use.

The potential applications of such indicators are manifold. They might provide the authorities involved in the AML system with an additional tool to carry out their activities of prevention or contrast of TBML on the basis of a robust risk-based approach. This is compliant with the international AML standards (FATF's Recommendation no. 1), which requires that "*countries perform a national assessment (NRA) of the risk of money laundering (and terrorism financing) so as to design proportional AML measures and re-allocate resources in the most effective way*". More specifically, the same authorities might benefit from the results of this analysis by raising their awareness on specific product lines and Italy's foreign trade partners, on the basis of the lists of anomalous commercial 'routes'.

The econometric analysis developed above aims at identifying the role played by relevant 'structural' variables – different from the factors underlying deliberate misreporting – in explaining misalignments in trade mirror statistics. The next step requires to isolate the unobserved sources of discrepancy which are held to be associated with illicit capital flight, in order to derive our indicators of TBML risk. To that end, the analysis has been focused on the systematic residuals of Model 3.

Indeed, within our model the risk indicators are simply identified as the country-4 digit random effects $\hat{u}_{jc}$, which measure the systematic residual component due to *c* and *j*-specific unobserved characteristics. They can be further interpreted as the share of the dependent variable that remains unexplained by the model once the structural determinants of observed trade statistics discrepancies are accounted for. In our approach, we have considered anomalous those observations belonging to the 2.5% right-hand tail of the overall random effects distribution (of which the top 20 positions are listed in Table 4, by way of example[27]).

Table 4 shows that the more relevant misreporting scheme among our anomalous cases is by far import-over-reporting, which is consistent with two previous findings of the regression estimates: the higher propensity to using that scheme to transfer capital abroad with respect to export under-invoicing is also reflected by the *EXPORT* negative coefficient estimate as well as by the greater magnitude of the scale variable coefficients referring to the import cases, either in terms of country-4 digit means and country-6 digit deviation (see Table 3).

In order to provide the indicative magnitude of the illicit financial flows measured by our indicators, it is possible to compute the estimated monetary value of anomalous discrepancies. This is obtained by inverting and decomposing the dependent variable in equation [1] (the log of absolute trade discrepancies) as follows:

$$\widehat{discrepancy}_{ic} = exp(\widehat{\boldsymbol{\beta}}\boldsymbol{X}) + exp(\widehat{\boldsymbol{\beta}}\boldsymbol{X})[exp(\hat{u}_{jc}) - 1]$$

where $\boldsymbol{X}$ is the vector of covariates and $exp(\widehat{\boldsymbol{\beta}}\boldsymbol{X})$ is the evaluated fixed component of the model, while the second term represents the evaluated random component, which is the value indicated in the last column of Table 4.

From our micro-risk indicators, indicators at *country level* can be obtained as the share of the 4-digit sectors identified as outliers (top 2.5% of the random effects total distribution) for each of Italy's partner country on the total number of existing 4-digit sectors for which trade is observed between Italy and that country.

Several "offshore" countries, like Cayman and British Virgin islands, are excluded from the analysis due to the lack of mirror data (see footnote 14). Hence, the list of countries (24 in total) for which the synthetic indicator is statistically significant (see Table 5) includes many of Italy's main trade partners, mainly European Union (and euro area) member states: the 24 riskiest countries (according to our indicator) accounted for almost 60% of Italy's external trade in the period of analysis, which is consistent with what most contributions in the relevant literature point out, that is anomalous trade flows are frequently observed *vis-à-vis* major trade partners (see Bhagwati, 1981; Pitt, 1981; Ferwerda *et al.*, 2013). This result can be reconciled with the negative sign of the EU dummy coefficient in Table 3: anomalous transactions tend to be greater with non-EU countries (hence the negative sign of the coefficient), but are more often observed with reference to EU member states, with whom trade flows are more frequent.

[27] The total number of country-product trade flows is 82,142 which correspond to the number of random effects estimated by the reference Model 3.

Table 4
Anomalous trade flows at country-sector (4 digit) level
(2010-13; top 20 positions[a])

Country	4-digit sector	4-digit sector (description)	Prevailing type of mis-reporting[b]	Estimated anomalies (mls dollars)
Ireland	2934	Nucleic acids and their salts, whether or not chemically defined; other heterocyclic compounds	import over-reporting	108
Denmark	5503	Synthetic staple fibres, not carded, combed or otherwise processed for spinning	import over-reporting	35
Israel	2710	Petroleum oils and oils from bituminous minerals, not crude; (…)	import over-reporting	189
China	5102	Fine or coarse animal hair, not carded or combed	import over-reporting	204
United Kingdom	8803	Aircraft; parts of heading no. 8801 or 8802	import over-reporting	307
Netherlands	2941	Antibiotics	import over-reporting	116
Egypt	5205	Cotton yarn (other than sewing thread), containing 85% or more by weight of cotton, not put up for retail sale	import over-reporting	108
Austria	2846	Compounds, inorganic or organic, of rare-earth metals; (…)	import over-reporting	12
Ireland	2922	Oxygen-function amino-compounds	import over-reporting	20
Germany	2716	Electrical energy	import over-reporting	782
Ireland	2941	Antibiotics	import over-reporting	69
United Arab Emirates	1514	Rape, colza or mustard oil and their fractions; (…)	import over-reporting	66
China	9102	Wrist-watches, pocket-watches, stop-watches and other watches, (…)	import over-reporting	185
Netherlands	2942	Organic compounds; n.e.c. in chapter 29	import over-reporting	5
Rep. of Korea	2929	Nitrogen-function compounds, n.e.c. in chapter 29	import over-reporting	9
Egypt	7208	Iron or non-alloy steel; flat-rolled products of a width of 600mm or more, hot-rolled, not clad, plated or coated	import over-reporting	124
Singapore	8542	Electronic integrated circuits	export under-reporting	727
Egypt	7606	Aluminium; plates, sheets and strip, thickness exceeding 0.2mm	import over-reporting	107
Austria	8405	Generators for producer or water gas with or without their purifiers acetylene (…)	import over-reporting	78
Netherlands	2906	Alcohols; cyclic, and their halogenated, sulphonated, nitrated or nitrosated derivatives	import over-reporting	47

[a] The total number of *random effects* coincides with the number of groups considered by the main model of Table 3 (81,142).
[b] For each combination of country and (4-digit) sector both cases of import over-reporting and export under-reporting can be observed. The table reports the type which is prevailing in size.
Source: authors' own calculations.

As an alternative approach, one could consider the ranking of countries coming from the aggregation of the monetary (estimated) value of anomalous discrepancies; Table 5 also provides the list of countries showing the largest size of our model-based estimates of anomalous illicit trade flows. As expected, in this case the major commercial partner of Italy are ranked at the top of the distribution.

Table 5
Riskiest countries
(2010-2013; based on top 2.5% country-4 digit flows)

Countries	Share (%) of anomalous country-4-digit flows	Estimated anomalies[a] (mls dollars)	Estimated anomalies rank	Country's share of Italy's trade[b] (%)
Luxembourg	8.7***	508	23	0.2
China	7.6***	6,880	1	5.0
Netherlands	7.3***	3,320	4	4.2
Egypt	7.3***	1,380	8	0.7
Saudi Arabia	7.9***	597	18	0.5
Austria	5.8***	754	13	2.5
United Kingdom	5.6***	1,220	9	4.0
Ireland	5.6***	645	16	0.6
Germany	4.9***	3,320	3	15.0
Denmark	5.0***	541	21	0.6
France	4.4***	2,440	5	10.6
Sweden	4.5***	175	48	1.0
Tunisia	4.6***	764	12	0.8
Spain	3.9***	689	15	5.1
Japan	4.0***	2,430	6	1.2
Belarus	4.0**	101	59	0.1
Bosnia and Herzegovina	3.7**	77	66	0.1
Greece	3.5**	383	29	0.9
Hong Kong	3.5**	481	24	0.7
Israel	3.4**	388	28	0.4
Cambodia	5.0**	110	56	0.0
Ukraine	3.5*	289	36	0.5
Belgium	3.2*	590	20	3.4
Finland	3.3*	104	58	0.4
…				
Russian Federation	2.2	4,160	2	0.1
USA	2.0	2,340	7	5.1
Iran	1.4	999	10	0.5

p-value: *** <0.01, ** <0.05, * <0.1 (statistical test: share of anomalies > 2.5).
Sample: 152 countries included in the analysis (see footnote 14 for details).
[a] Sum by country of the estimated discrepancies corresponding to the anomalous financial flows (top 2.5%).
[b] Percentages refer to Italy's import and export total values recorded in the COMTRADE database (2010-2013).
Source: authors' own calculations.

The procedure applied to partner countries can be similarly repeated with reference to aggregate sectors. Specifically, for each 2-digit sector we consider the share of anomalous flows on the total number of observed country-4 digit commercial flows.

The list of the riskiest sectors (see Table 6) shows a strong presence of both manufactured products – chemical, pharmaceutical products, foodstuffs and textiles – and raw materials like crude oil, vegetable products and metals (steel and iron); in other words, the type of merchandise featuring potentially anomalous flows is extremely varied, reflecting Italy's complex and diversified trade structure, with many products featuring a non-negligible share of Italy's external trade.

Table 6
Riskiest sectors
(2010-2013; based on top 2.5% country-4 digit flows)

2-digit sector	2-digit sector (description)	Share (%) of anomalous country-4 digit flows	Estimated anomalies[b] (mls dollars)	Share of total Italy's trade[a] (%)
29	Organic chemicals	6.5***	1,950	2.5
28	Inorganic chemicals; organic or inorganic compounds of precious metals, (…)	5.3***	364	0.5
8	Edible fruit and nuts; peel of citrus fruit or melons	6.2***	99	0.7
27	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	6.8***	9,240	10.3
72	Iron and steel	4.3***	1,500	3.5
30	Pharmaceutical products	5.6***	3,730	4.2
4	Dairy produce; birds' eggs; natural honey; (…)	4.7***	202	0.8
11	Products of the milling industry; malt; starches; inulin; wheat gluten	4.7***	44	0.1
16	Preparations of meat, of fish or of crustaceans, molluscs or other aquatic invertebrates	5.1***	201	0.3
71	Natural or cultured pearls, precious or semi-precious stones, precious metals, (…)	3.8***	2,550	2.8
22	Beverages, spirits and vinegar	3.7**	130	1.1
55	Man-made staple fibres	3.6**	191	0.3
51	Wool, fine or coarse animal hair; (…)	3.8**	413	0.4
79	Zinc and articles thereof	4.8**	133	0.1
35	Albuminoidal substances; modified starches; glues; enzymes	4.1**	52	0.2
38	Miscellaneous chemical products	3.3**	213	1.2
47	Pulp of wood or of other fibrous cellulosic material; recovered (waste and scrap) paper or paperboard	4.7**	90	0.3
15	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	3.4**	158	0.6
24	Tobacco and manufactured tobacco substitutes	5.3*	65	0.3
33	Essential oils and resinoids; perfumery, (…)	3.6*	153	0.7
61	Articles of apparel and clothing accessories, knitted or crocheted	3.2*	1,160	1.6
13	Lac; gums, resins and other vegetable saps and extracts	4.9*	40	0.0
18	Cocoa and cocoa preparations	4.1*	126	0.3
36	Explosives; pyrotechnic products; matches; pyrophoric alloys; certain combustible preparations	4.5*	17	0.0

p-value: *** <0.01, ** <0.05, * <0.1 (statistical test: share of anomalies > 2.5).
Sample: 152 countries included in the analysis (see footnote 14 for details).
[a] Percentages refer to Italy's import and export total values recorded in the COMTRADE database (2010-2013).
[b] Sum by 2-digit sector of the estimated discrepancies corresponding to the anomalous financial flows (top 2.5%).
Source: authors' own calculations.

5.2 Anomalies characterisation

In order to characterise our results more precisely in terms of the type of country more liable to be potentially linked to TBML, we have developed a multivariate correlation analysis between our country-level risk indicator and some indicators of country's opacity or financial attractiveness.

As was previously explained, we intentionally chose not to include such variables in our model for a variety of reasons: any set of indicators, for exhaustive as it may be, is likely to fall significantly short of accounting for all rationales underlying illegal trade; indicators reliability suffers from measurement errors or approximations; basing our risk indexes on a model including country indicators would be tantamount to risk-ranking countries on the sole basis of the latter.

Hence our determination to adopt a 'residual approach' and turn to indicators somehow related to illegal activities only at this stage of the analysis.

The first indicator taken into account is Transparency International's Corruption Perception Index (CPI), which ranks about 140 countries on a yearly basis according to which extent corruption is perceived to be widespread in each. We considered data for 2013,[28] our benchmark year in the econometric model.

We also deployed an indicator of countries' overall risk of money laundering and terrorist financing, the Basel AML Index. It varies between 0 and 10 (maximum level of risk) and is obtained by the Basel Institute on Governance as a weighted average of 14 elementary indicators concerning a wide range of items, from AML/CFT regulation to corruption, from financial standards to political disclosure and rule of law.[29] The year of reference for this indicator is 2014, the year covering most countries of our sample.

Finally, we also included in the multivariate correlation of our risk indicator an index of economic attractiveness and institutional stability, the *Business protection from crime and violence Index*,[30] which is a component of the World Economic Forum's Global Competitiveness Index (the higher the index, the more attractive a country is in economic and financial terms).

The three indices are then used as covariates in a regression featuring our country risk indicator as dependent variable (including only countries featuring at least one anomalous trade flow; see Table 7). In this respect, both indicators in Table 5 (the share of anomalous trade flows and the estimated monetary anomalies) are separately included as dependent variables.

In the regressions including the three indices of opacity, the coefficients are not significant for Perceived Corruption and Money Laundering Risk, whilst significantly positive for the Business protection from crime and violence. Though counter-intuitive at a first sight, this result should not be surprising if we scrutinise more closely the countries that each index ranks worst. These territories feature low levels of international trade (at least with Italy) and, more importantly, their political, social and economic development is in general so low to make most financial investments, both of the legal and illegal kind, definitely unsafe and unprofitable. Since illegal trade typically takes place alongside legal trade, as repeatedly claimed in literature, it would be surprising to find any illicit trade where there are no legal trade flows altogether or just tiny trickles thereof.

Accordingly, if one includes among the regressors also a proxy of Italy's bilateral trade size - in terms of value (Models b) or number of 6-digit traded products (Models c) - our risk indicators increase with the measure of economic attractiveness and institutional stability[31] and with the risk of money laundering: in other words, countries which are more attractive to criminals for TBML purposes are those among Italy's established trade partners featuring adequate levels of opacity, but still granting reassuringly high standards of rule of law.[32]

[28] Since the methodology of definition of the CPI varies in each year, we transformed the original distribution by its standardized fractional rank, thus obtaining an index annually varying between 0 (minimum corruption) and 1 (maximum corruption).

[29] The weight assigned to AML is set equal to 65% (for further details, see https://index.baselgovernance.org/).

[30] The index covers a sample of around 130-140 countries and is derived from the following Executive Opinion Survey question (World Economic Forum): "*In your country, to what extent does the incidence of crime and violence impose costs on businesses? [1=to a great extent; 7=not at all]*. We changed the original definition of *Business 'cost of' crime and violence* to *Business 'protection from'* to increase the significance, from our perspective, of the associated country rankings it gives rise to; indeed, the index ranks best those countries with higher financial and economic attractiveness. For further details see http://reports.weforum.org/global-competitiveness-report-2015-2016/.

[31] As opposed to the other country indexes, the top 50 countries according to the *Business cost of crime and violence* cover nearly 70% of Italy's external trade.

[32] Regressions were also run for a set of countries including those with no anomalous discrepancies altogether. Results were patently unsatisfactory and scarcely insightful: since this lot includes mainly developing countries with no trade

Table 7
Anomalies and country features

Dep. Var.	Share of anomalous country-4 digit flows			Estimated anomalies (mls dollars)		
	Model 1a	**Model 1b**	**Model 1c**	**Model 2a**	**Model 2b**	**Model 2c**
Perceived Corruption	-0.399	0.071	-0.177	-1.855	-0.144	-1.043
Money Laundering Risk	0.024	0.064	0.178**	0.292	0.438***	0.857***
Business protection from crime and violence	0.216**	0.163**	0.168**	0.440*	0.249*	0.266
Ln(Trade with Italy)		0.278***			1.012***	
Ln(Number of 6-digit sectors)			0.802***			2.928***
Constant	-5.083***	-4.834***	-12.132***	15.388***	16.291***	-10.365***
R^2	0.122	0.432	0.320	0.104	0.702	0.489
N	102	102	102	102	102	102

p-value: *** <0.01, ** <0.05, * <0.1.
Source: authors' own calculations.

6. Concluding remarks

Authorities and operators in the field of fighting money laundering and financial crime have sounded the alarm on the widespread use of international trade as a reliable and effective channel for the cross-border transfer and the consequent laundering of their ill-gotten gains.

The lack of appropriate analytical tools have long dogged preventive actions devoted to the detection of trades of this sort and of the illegal financial flows underlying them; more analysis might complement and support the activity by investigative bodies, itself focused on the repressive phase of illegal conducts.

The aim of this paper is to come to the rescue in this very respect. Far from being the first contribution from this viewpoint, our work relies on a consolidated strand of literature whose attention has been mainly devoted to the analysis of the inconsistencies in trade statistics that may potentially provide useful hints of TBML-related illegal flows.

By making use of COMTRADE mirror statistics for Italy's trade flows from 2010 to 2013 at the maximum level of goods classification for each partner country, a linear mixed model is estimated trying to account for the main determinants of discrepancies between mirrored data. Based on previous works in this field, we identify a group of explanatory variables accounting for inefficiencies in the reporting system in the partner country (linked to its level of economic development) and possible misalignments of product classification (that are normally the consequence of the lack of trade agreements between two countries or arise from the paucity of mutual trade flows).

Thus the model factors in countries' and products' structural features that may give rise

whatsoever with Italy, results essentially confirm that illegal trade routes mimic legal trade ones. The regression featuring only country risk indicators yields a negative coefficient for Money laundering risk and a positive one for Business protection from crime and violence (Perceived corruption is non significant), whilst including also our proxy of Italy's bilateral trade size makes all other variables statistically non significant. The interpretation of such results seems straightforward: anomalous discrepancies are observed only if and when there is some trade, which typically takes place with countries with a relatively low degree of opacity and a high degree of financial attractiveness and institutional stability.

to trade statistics inconsistencies, enabling us to identify the residual effects triggered by factors possibly related to illegal financial flows. Two specific features make our approach particularly innovative: i) the correction of trade data for the *cif/fob* discrepancy relies on point estimates for freight costs at an extremely detailed level of accuracy, instead of applying an invariable (and implausible) one-size-fits-all correction coefficient to all data; ii) the end outcome of the study is the definition of country-product indicators of TBML risk, that may be applicable for the detection of potential money laundering commercial transactions.

The estimates obtained are consistent with the literature and the theory. Based on the model's random effects, we compute risk indicators at a country-4 digit level, leading to the compilation of rankings. All rankings seem to be basically consistent with day-to-day experience of authorities in the field. We also developed a multivariate correlation analysis of our risk indicators with some widely deployed country indices associated to illegal activities: results show that, once the size of trade flows between Italy and its partners is controlled for, anomalies increase with the degree of opacity of the counterpart, but also with a measure of its financial attractiveness and institutional stability. In this respect, criminals seem to behave just like any other investor, seeking a safe haven to his or her assets. It is worth adding, though, that our work relies on trade flows, but the actual direction of the underlying financial flows may be completely different, as in the case presented at the very beginning of our study.

Our analytical framework could be fruitfully expanded in two directions.

Our methodology could be applied to data concerning exchanges in intangible products, such as services, which − just because they cannot be reliably weighted, counted and measured − are certainly more suitable to be used for ill-intended reporting tricks.

Secondly, the capacity of the approach to actually detect illicit trade flows could be highly enhanced should one be able to make use of data on single import-export transactions, which customarily are available to customs authorities. That, for one thing, could allow to compute the actual average prices applied to each transaction, which can then be compared to market prices so as to identify statistical outliers, i.e. transactions featuring prices significantly different from the ongoing market quotes: that is an approach which is already adopted by customs authorities in some countries and which could be made more effective by applying model-based risk indicators. In addition, information on single transactions that would include the parties to those transactions could be matched with a wide array of firm-level data so as to establish correlations and patterns, which again could result in the identification of anomalous trades on the basis of the apparent inconsistency between the size of the transaction and the financial standing and the economic features of the parties involved.

These developments would very much mimic the one illustrated in the present study in that both would lead to the definition of statistic-based analytical tools to be deployed for day-to-day operations and checks by authorities and operators in the field of customs controls and money laundering prevention so as to enhance the effectiveness of such activities.

Appendix

Data sources

Database COMTRADE (http://comtrade.un.org/db/mr/daPubNoteDetail.aspx): it contains detailed imports and exports statistics reported by statistical authorities of close to 200 countries or areas. It concerns annual trade data from 1962 to the most recent year. UN Comtrade is considered the most comprehensive trade database available with more than 1 billion records. A typical record is – for instance – the exports of cars from Germany to the United States in 2004 in terms of value (US dollars), weight and supplementary quantity (number of cars). The database is continuously updated. Whenever trade data are received from the national authorities, they are standardized by the UN Statistics Division and then added to UN Comtrade (data downloadable from http://comtrade.un.org/db/dqQuickQuery.aspx)

Database on international trade tariffs (source World Bank): data broken down by year/country/product (6-digit classification)/flow (import/export), downloadable from (after registration): https://wits.worldbank.org/WITS/WITS/Restricted/Login.aspx.

Gravity variables: the source is the well-known **CEPII**, a French research center in international economics which produces studies, research**,** databases and analyses on the world economy and its evolution. It was founded in 1978 and is part of the network coordinated by the Economic Policy Planning for the Prime Minister. The database we used are "GeoDist" e, mainly, "TRADHIST", in order to select some variables (like distance and belonging to a an economic area); downloadable from (after registration): http://www.cepii.fr/CEPII/en/bdd_modele/bdd.asp.

Database for the conversion of imports from *cif* to *fob* values: we used data from the survey on international merchandise transport of Italy. On the basis of the freight rates coming from the survey, we are able to calculate the transport (and insurance) cost as a percentage of the value of imported/exported goods (*ad valorem* cost) by year, partner country and NST2007 product classification, which is converted to 6-digit in order to be applied to COMTRADE data; the *ad valorem* cost is applied both on Italian imports and on partner country's imports. In detail, since 1999 the Bank of Italy sample survey collects data from transport enterprises, which are interviewed to get information about average costs of international merchandise transport (from/to Italy) broken down by the direction of flow (import/export), the mode of transport and type of load (container, dry or liquid bulk, etc.), the type of goods (when relevant) and the partner country (or geographical zone). About 150 transport enterprises are interviewed every year; they are sampled after a stratification into eight categories, defined according to their operational characteristics: 1) road transporters; 2) multimodal operators; 3) ship brokers; 4) ship companies specialised in containers; 5) rail companies; 6) intermodal rail-road companies; 7) air companies; 8) air brokers. Enterprises are selected within each group and they are extracted from lists published by transport associations and/or transport specialised publications, which also report rankings based on turnover or number of employees; a further stratification is based on other variables like turnover and geographical allocation. Transport operators supplies data also on insurance costs; moreover, on the basis of a transport model average distances are estimated and, consequently, freight rates are broken down in "three legs" − within the exporting country, within the importing country and in third countries – in order to obtain a *cif-fob* conversion by partner country (or geographical area); for further details, see Pastori *et al* (2014) and (in English) Bank of Italy (2016).

World Development Indicators (source World Bank): the primary World Bank collection of development indicators, compiled from officially-recognized international sources. It presents the most current and accurate global development data available, and includes national, regional and global estimates http://data.worldbank.org/data-catalog/world-development-indicators.

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