Draft paper.
Please, do not cite or circulate without the authors' permission

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

Misreporting tricks of different sort applied to the transfer of goods between different countries have become increasingly exploited by criminals worldwide for money laundering ends. The main international anti-money laundering organisations started paying attention to this phenomenon, dubbed 'trade-based money laundering' (TBML), a long time ago, but the lack of appropriate analytical tools have reportedly dogged preventive actions. Nonetheless, literature have widely advocated the possibility that the analysis of inconsistencies in mirrored bilateral trade data could provide some help. By treading on the footsteps of previous authoritative contributions in the field, this work sets up a linear mixed model factoring in the main structural determinants of discrepancies between mirrored data concerning Italy's 2010 to 2013 external trade at a highly detailed level of goods classification for each partner country. Point estimates of freight costs are used to net each observation of the correct *cif*/*fob* discrepancy. The regression estimates are then deployed in order to compute TBML risk indicators at a country/product level. Based on the indicatorsseparate lists of countries and product lines can be compiled, which may be used for a risk-driven search of potential illegal commercial transactions.

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

* UIF (Italian Financial Intelligence Unit), Bank of Italy, Analysis and Institutional Relations Directorate.
** Bank of Italy, Directorate General for Economics, Statistics and Research.

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 study, illustrates quite effectively 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 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 that one can have in mind 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 fund 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 movement of funds corresponding to the payment thereof may be connected to the proceeds from the supply of illegal goods and services, such as drugs, weapons or in connection with human beings trafficking or kickbacks, or to create legitimate 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 particularly 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. Not unlike what famously happens in fairy tales, also in this field mirrors may turn out to

[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 Domenico J. Marchetti, an anonymous referee, the seminar participants at UIF, 2016 SIDE-ISLE Conference in Turin (December 2016), and Eurostat meeting on Illegal Economic Activities in National Accounts and Balance of Payments (March, 2017).

[2] The case is taken from Financial Action Task Force (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, services are indicated as one of the potential further avenues of our research in the concluding sections of the paper.

possess extremely powerful properties in detecting menaces of some sort.

Alongside purposeful misevaluation of goods, another possible source of discrepancies 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 certainly 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 diverse goods classification criteria, less frequent when countries are regular commercial partners or take part 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 different, albeit 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 goods classification for each and every 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 thereof) and possible misalignments of product classification (due to the lack of trade agreements or infrequent trade flows).

Our work improves from the existing literature in three main directions. Firstly, import and export values are adjusted for *cif/fob* discrepancies with point data based on 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 (HS 6 digit) and several country-level characteristics accounting for structural determinants of trade statistics 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 practitioners 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, while Section 3 describes the overall conceptual framework and the data used in the analysis. Section 4 sets out the econometric model estimated 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 product-country pairs, countries and 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 concur 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 and foremostly 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 typological 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 firmly 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) take 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 and every 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.

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

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 and of destination of the goods that is reported incorrectly). To this two instances, one has to add deliberate misinvoicing, which is a type of misreporting involving either the quantities of goods being exchanged or the price applied to the exchange (Bhagwati, 1981).

Most studies analysing mirror statistics disparities with the aim of explaining the determinants thereof do not adopt a wholesale approach to the issue. Thus, just to mention a few, Carrère and Grigoriou (2014) mainly examines 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, in general terms), that is, imports over-reporting and export under-reporting.

Most of the studies reviewed 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. Likewise Patnaik et al. (2012) add to this lot also 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 so-called 'residual' approach':[4] 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 illicitly deliberate trade misreporting.

Such an approach secures two advantages from that taken in other studies. Firstly, any explanatory variable that may be included in the model so as to control for illegal trade risks accounting for the drivers that may actually explain it only to very limited extent: for instance, both Carrère and Grigoriou (2014) and Berger and Nitsch (2012) in their models use indicators of

[4] We apply a methodological development of two preceding studies, where money-laundering risk indicators are derived on the basis of regression residuals (see Cassetta *et al.*, 2014; Ardizzi *et al.*, 2016).

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 analyse the estimate residuals may be the best option to capture their effects.

Secondly, such approach serves extremely well the main purpose of our work. It need stressing that 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 goal is of far smaller scale though in our view no less ambitious: 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.

In another relevant respect our work improves on previous studies. We make use of the results of the yearly sample survey on international merchandise transport that the Bank of Italy has carried out since 1999, which estimates freight rates according to the structure of the reference market (for further details, see Pastori *et al.,* 2014, and Bank of Italy, 2016). Hence, the survey provides point estimates for freight costs at an extremely detailed level of accuracy, enabling us to aptly 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 in trade data 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. Moreover, by under-reporting her sales abroad, the exporter can add some unreported foreign currency-denominated profits to her official ones.
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 exports over-reporting is that it may be exploited so as to bring back illicit capitals detained outside the country.

[5] As noted by Nitsch (2016), "*This 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*".

3. The most influencing factor for **under-reporting of Italy's imports** is a 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 underlying determinant giving rise to **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 focussed our analysis on the hypotheses described under 1 and 4.

It need stressing that misreported trade flows of the kind we are scrutinising here may give rise to trade data asymmetries, but this is not necessarily the case. In the first instance, misreporting through misinvoicing can produce opposite effects that may cancel each other: "[…] *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). 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.

Secondly, irregular transfer pricing conducts in the context of intra-group transactions are likely not to be reflected in trade data asymmetries, 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)*". As such, therefore, this illicit conducts, which are often benevolently included into the realm of multinationals' tax optimisation policies, are not captured by our radar and consequently fall beyond the scope of our analysis.

Anyway, regardless of the caveats of this kind, from an analytical point of view it remains uncontroversially interesting to examine trade discrepancies in order to detect possible regularities which could hide financial flows of illegal origins. As we are interested in deliberate misreporting by traders, the way to proceed is to appropriately isolate the effect of the structural differences and the errors committed by customs offices. To do so, we have to find the right proxies.

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 that may reasonably represent channels allowing for funds to be illegally funneled abroad. Formally, we therefore only considers those instances in which:

(I) $\boldsymbol{E_{ih} - M_{ph} < 0} \quad \forall \boldsymbol{p, h}$ (under-reporting of Italian exports)

(II) $\boldsymbol{M_{ih} - E_{ph} > 0} \quad \forall \boldsymbol{p, h}$ (over-reporting of Italian imports)

with E=export, M=import (*fob*), i=Italy, p=partner country, h=product classification (HS 6-digit[6]).

Discrepancies in mirror statistics of this kind are, first of all netted of the *cif/fob* distortions (relying on the Bank of Italy merchandise transport survey – see below) and then taken in logs and with appropriate positive sign (absolute discrepancies: DEV_ABS).

As stated in previous sections, we take what we dub as a 'residual approach'. In order to explain 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 identified in literature (see

[6] Products classification downloadable at https://unstats.un.org/unsd/tradekb/Knowledgebase/41.

Table 1[7]), and then take the estimate residuals (or a specific part thereof) as measures of the illegal component of such discrepancies.

Hence, 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 trade statistics reporting system. GDP is taken at 2005 constant dollar value and may be expected to have a negative relationship with trade statistics gaps.

Also 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 and exchange trade data on a regular basis. Thus, one can expect that the larger the distance between Italy and its 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 (or RTA) of some sort. Being members of the same economic or trade club generally involves also sharing common 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, whereby a high share thereof not only are signatories to the European Union treaties, but also share a common currency and are thus members of the euro area. Hence, in an alternative specification of the model (see Table 2 below) the variable *UE* takes up three modalities: no RTA, EU member and Euro area member, with the last two expected to feature a negative relationship with the dependent variable if set against the first.

A country's openness is also another driver to be taken into account. As was pointed out above, some pivotal contributions in 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 partner country's openness (*TROPEN*).

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

Firstly, we account for the tax regime in each of Italy's partner country by taking into account the total tax rate on commercial profits (*TAX*[8]). 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 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, such conducts as 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[9] are cleansed of flows that may be associated to tax evasion. Indeed, our focus is on

[7] Table 1 also lists the time lag (differences in the timing of reporting or recording of 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.

[8] For 32 country-year cases, missing values have been imputed with the closest value available.

[9] As specified in Section 2, we refer to TBML as the "the process of disguising the proceeds of crime by moving value through the use of trade transactions" irrespective of the nature of the misrepresentation scheme, being it false price, quantity or quality of imports or exports.

specific types of illegal trade flows, when 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 in having final indicators which are net of effects which falls 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 own imports from foreign countries. Custom tariffs[10] (*TARIFF*) applied by Italy's partner countries for each line of product (at HS6 digit level) feature as an additional covariate of the model, whose role is that of 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 product line. Firstly, the mean of the value of trade between Italy and each partner country with reference to a broader product line (HS4) than the one at which the dependent variable is defined (HS6) is taken into account, so as to allow for between-effects relative to different product lines. At the same time, the deviance from such mean is also introduced in order to allow for product line-specific within-effects.

Finally, the model also features dummies for the broadest definition of product lines (HS2) 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 HS level[11] The data are collected by the United Nations from national agencies which transmit figures in national currencies or US dollars. Figures in national currencies are converted into US dollars using monthly exchange rates. We took data concerning Italy's foreign trade from 2010 to 2013.[12] In a few cases some partner countries did not report any trade with Italy in a whole year, making it thus 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).

---

[10] This variable is defined as the average between the Most Favored Nation (MFN) tariff and the Effectively Applied (AHS) tariff applied to each country and HS6 pair. Country-year missing values have been set equal to a value just above zero (1E-09) in order to avoid indefinite log transformations.

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

[12] 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 for 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).

As for gravity variables (distance and regional trade agreement), we used the well-known **CEPII** database,[13] a French research centre in international economics which produces studies, research**,** databases and analyses on the world economy. The data source for GDP per capita and tax rate is the **World Development Indicators** published by the World Bank.[14]

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[15]). The tariff information is available at the 6-digit Harmonized System (HS) 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 modelling* 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.[16] 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 estimates the corresponding *random effects* in addition to the population-averaged fixed effects.

Consider the theoretical framework described in Section 3.2 and the hierarchical structure of the data arising once elementary units defined at country-HS6 digit of products classification ($i = 1, \dots, n_j$) are considered nested and so collapsed across clusters of country-HS4 digit of products classification ($j = 1, \dots, J$). The dependent variable is defined as the natural logarithm of the absolute discrepancies observed – at the most detailed level of country-product classification – between import (export) trade statistics recorded in Italy and the corresponding export (import) values gathered by each commercial partner. We suggest the following basic specification of a *two-level random intercept model*:[17]

$$
\begin{aligned}
dev\_abs_{ijc} = {} & \beta_0 + \beta_1 tax_c + \beta_2 gdp_c + \beta_3 tropen_c + \beta_6 tariff_c + \beta_4 dist_{\bar{c}} \\
& + \beta_5 UE_{\bar{c}} + \beta_7 HS2_i + \beta_8 EXPORT_i \\
& + \beta_9 under\_exp_i + \beta_{10} over\_imp_i + \beta_{11} \overline{under\_exp}_j + \beta_{12} \overline{over\_imp}_j \\
& + u_j + \varepsilon_{ij} \qquad [1]
\end{aligned}
$$

where all the continuous covariates (indicated in lowercase letters) have been transformed

[13] http://www.cepii.fr/CEPII/en/bdd_modele/bdd.asp.
[14] http://data.worldbank.org/data-catalog/world-development-indicators.
[15] https://wits.worldbank.org/WITS/WITS/Restricted/Login.aspx, after registration.
[16] 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.
[17] It is the simplest form of *linear mixed model.*

in their natural logarithms. The subscript $\bar{c}$ refers to country-specific variables which are invariant across years. The variables *UE, HS2* and *EXPORT* are categorical variables respectively referring to:

- no RTA, EU (not Euro area) membership, and Euro area membership;
- HS2 aggregated international classification of products;
- the case of under-reporting of Italian exports (*EXPORT*=1) as opposed to over-reporting of Italian imports (*EXPORT*=0).

The reason for including the '**size variables**' *under_exp* and *over_imp*, taken as deviation from the respective cluster-*j* means – in turn explicitly considered in the equation – is twofold: on the one hand, they allow to take into account scale effects due to heterogeneous HS6-trade values magnitude between Italy and each trade partner country (separately for Italian imports and exports); on the other hand, possible endogeneity problems due to cluster-*j* heterogeneity bias of the same variables are explicitly controlled for.[18]

The regression coefficients β_k (k=1,…,12) represent the conditional (fixed) effects of the independent variables given the values of the random effects u_j, which in turn can be interpreted as measuring HS4-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 $\varepsilon_{ij}|x_{ij} \sim N(0, \sigma_\varepsilon^2)$, $u_j|x_{ij} \sim N(0, \sigma_u^2)$.

Thus, a fundamental assumption in random intercept models is that of independence between covariates and cluster residuals ($E[u_j|x_{ij}] = 0$). 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.[19] 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 research interest focusses in cluster specific effects. All this three criteria are fully met in our case, definitely supporting the choice of a random effects estimation. In particular, a) the 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;[20] b) many of the model covariates are defined at country or product level; c) our final objective is that of defining TBML risk indicators as resulting from the model's random effects (or rather the empirical Bayes estimates thereof).

4.2. Estimation results

The following Table 2 presents the baseline results obtained by the implementation of the random effects model [1]. The first two columns correspond to simpler alternative specifications of our benchmark (Model 3) which differs from the other two because of the

---

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

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

[20] Unlike the case of fixed effect specification, samples made of *singleton*-cluster are indeed 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).

inclusion of the covariate on partner-country commercial taxes (*tax*) and the additional *UE* category of 'Euro area membership'. Anyhow, 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 regression 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 *UE/UME* 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 and separately, to a trade discrepancy increase ranging between 0.1% and 5.8%.

Table 2
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***
UE†	-0.062***	-0.043***	-0.079***
			-0.014*
EXPORT	-1.799***	-1.793***	-1.798***
HS2	Yes	Yes	Yes
Scale variables			
OVER_IMP	0.826***	0.826***	0.826***
UNDER-EXP	0.074***	0.074***	0.074***
M_OVER_IMP	0.805***	0.805***	0.805***
M_UNDER-EXP	0.119***	0.119***	0.119***
year: 2010	0.051***	0.048***	0.048***
year: 2011	0.038***	0.036***	0.035***
year: 2012	0.007*	0.004	0.004
ConstantConst	1.193***	1.249***	1.282***
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-HS4)	0.180	0.181	0.181

Benchmark: *not UE country*, *over-evaluation of Italian imports*, *year 2013*.
Regression variable: *dev_abs*. All variables are in log, except UE.
† Assumes two values in Model 1 and 2 (*no RTA, EU member*) and also a third one (*UE not UME*) in Model 3.
*** p-value<0.01, ** <0.05, * <0.1.
Source: authors' own calculations.

Finally, all the 'auxiliary' scale variables accounting for imports/exports size (both in HS4-country means and corresponding HS6-country deviance) show positive and significant relation with our variable of interest, validating the correct inclusion of such scale effects.

Obtaining regression coefficients estimate that match the theoretical hypothesis is obviously important to our end.[21] 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 2 indicates that 18% of the total model variability can be attached to the specific country-HS4 intercepts.[22] This properly allows us to rely on their distribution for the definition of the anomaly indicators presented in the next section.

5. Indicators of anomaly

5.1 Residual analysis of country-product effects

It has repeatedly been stressed in the previous sections that our work has a prominent operational bias in that its main purpose is the definition of indicators of TBML risk.

The potential applications of such indicators are manifold. It 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 in the previous sections aimed 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 data 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 focussed on the systematic residuals of Model 3.

Indeed, the risk indicators are simply identified in the HS4-country random effects $\hat{u}_j$ of the model, which measure the 'systematic residual deviation' from the average response variable due to *j*-specific unobserved characteristics. They can be further interpreted as the share of the dependent variable that remains unexplained by the econometric 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 3, by way of example[23]).

The data show the more relevant misreporting scheme among our anomalous cases is by far import-over-reporting (see last column in Table 3) which is consistent with two previous findings of the regression estimates: the higher propensity to using that scheme to transfer capital

---

[21] 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.

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

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

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 HS4-country means and HS6-country deviance (see Table 2).

Table 3
Country-products (HS4) list of anomalous financial flows (2010-13)

Italy's partner country	HS4 goods classification	HS4 goods classification (description)	Type of mis-reporting§
Country 1	2934	Nucleic acids and their salts, whether or not chemically defined; other heterocyclic compounds	import over-reporting
Country 2	5503	Synthetic staple fibres, not carded, combed or otherwise processed for spinning	import over-reporting
Country 3	2710	Petroleum oils and oils from bituminous minerals, not crude; preparations n.e.c, containing by weight 70% or more of petroleum oils or oils from bituminous minerals; these being the basic constituents of the preparations; waste oils	import over-reporting
Country 4	5102	Fine or coarse animal hair, not carded or combed	import over-reporting
Country 5	8803	Aircraft; parts of heading no. 8801 or 8802	import over-reporting
Country 6	2941	Antibiotics	import over-reporting
Country 7	5205	Cotton yarn (other than sewing thread), containing 85% or more by weight of cotton, not put up for retail sale	import over-reporting
Country 8	2846	Compounds, inorganic or organic, of rare-earth metals; of yttrium or of scandium or of mixtures of these metals	import over-reporting
Country 1	2922	Oxygen-function amino-compounds	import over-reporting
Country 9	2716	Electrical energy	import over-reporting
Country 1	2941	Antibiotics	import over-reporting
Country 10	1514	Rape, colza or mustard oil and their fractions; whether or not refined, but not chemically modified	import over-reporting
Country 4	9102	Wrist-watches, pocket-watches, stop-watches and other watches, other than those of heading no. 9101	import over-reporting
Country 6	2942	Organic compounds; n.e.c. in chapter 29	import over-reporting
Country 11	2929	Nitrogen-function compounds, n.e.c. in chapter 29	import over-reporting
Country 7	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
Country 12	8542	Electronic integrated circuits	export under-reporting
Country 7	7606	Aluminium; plates, sheets and strip, thickness exceeding 0.2mm	import over-reporting
Country 8	8405	Generators for producer or water gas with or without their purifiers acetylene gas generators and similar water process gas generators, with or without their purifiers	import over-reporting
Country 6	2906	Alcohols; cyclic, and their halogenated, sulphonated, nitrated or nitrosated derivatives	import over-reporting

§ For each country/HS4 pair both cases of import over-reporting and of export under-reporting could hypothetically be observed. In order to assign the most anomalous country-product trade lines identified to either misreporting scheme, the value share of the two different instances on the whole group of observations for each country/HS4 pair was measured. The scheme accounting for the highest value share is indicated in this column.

From our micro-risk indicators, those based on the model random effects for each country-HS4 pair, one can also build country level risk indicators, which were computed as the share of the product lines 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 product lines traded between Italy and that country.

As several "offshore" countries, like Cayman and British Virgin islands, are excluded from the analysis due to the lack of mirror data (see footnote 11), the list of countries for which the synthetic indicator is statistically significant (see Table 4) include many of Italy's main trade partners, mainly European Union (and euro area) member states: the TBML-riskiest countries (according to our indicator) averaged 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 in major trade partners (see Bhagwati, 1981; Pitt, 1981; Ferwerda et al., 2013). The regression negative sign of the *UE* dummy coefficient may be reconciled with this result: albeit the observed discrepancies tend to be greater with non-UE countries, (hence the negative sign of the coefficient) anomalous transactions are more often observed with reference to UE member states, with whom trade flows are more frequent.

Table 4
Risk ranking of Italy's trade partner countries (2010-13).
(based on top 2.5% of country-products(HS4) distribution)

Italy's trade partner country	Share (%) of anomalous trade lines	Value share of total Italy's trade§
Country 13	8.7***	0.2%
Country 4	7.6***	5.0%
Country 6	7.3***	4.1%
Country 7	7.3***	0.7%
Country 14	7.9***	0.5%
Country 8	5.8***	2.5%
Country 5	5.6***	4.0%
Country 1	5.6***	0.6%
Country 9	4.9***	14.8%
Country 2	5.0***	0.6%
Country 15	4.4***	10.5%
Country 16	4.5***	1.0%
Country 17	4.6***	0.8%
Country 18	3.9***	5.0%
Country 19	4.0***	1.2%
Country 20	4.0**	0.1%
Country 21	3.7**	0.1%
Country 22	3.5**	0.9%
Country 23	3.5**	0.6%
Country 3	3.4**	0.4%
Country 24	5.0**	0.0%
Country 25	3.5*	0.5%
Country 26	3.2*	3.4%
Country 27	3.3*	0.4%

*** p-value<0.01, ** <0.05, * <0.1 (statistical test: share of anomalies > 2.5).
§ Percentages refer to the Italy's import and export total values recorded in the COMTRADE database (2010-13).

The procedure applied to partner countries can be similarly repeated with reference to each product line. Specifically, for each 2-digit class of goods we consider the share of anomalous product-country trade-based financial flows on the total number of observed trade lines.

The list of the TBML-riskiest products (see Table 5) show a strong presence of both some 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 the complex trade structure of an open economy like Italy's, with many product lines featuring a relevant share of Italy's external trade.

Table 5
Risk ranking of HS2 product lines (2010-13)
(based on top 2.5% of country-products(HS4) distribution)

HS2 goods classification	HS2 goods classification (description)	Share (%) of anomalous trade lines	Share of total Italy's trade§
29	Organic chemicals	6.5***	2.5%
28	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare-earth metals, of radioactive elements or of isotopes	5.3***	0.5%
8	Edible fruit and nuts; peel of citrus fruit or melons	6.2***	0.7%
27	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	6.8***	10.3%
72	Iron and steel	4.3***	3.5%
30	Pharmaceutical products	5.6***	4.2%
4	Dairy produce; birds' eggs; natural honey; edible products of animal origin, not elsewhere specified or included	4.7***	0.8%
11	Products of the milling industry; malt; starches; inulin; wheat gluten	4.7***	0.1%
16	Preparations of meat, of fish or of crustaceans, molluscs or other aquatic invertebrates	5.1***	0.3%
71	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal and articles thereof; imitation, jewellery; coin	3.8***	2.8%
22	Beverages, spirits and vinegar	3.7**	1.1%
55	Man-made staple fibres	3.6**	0.3%
51	Wool, fine or coarse animal hair; horsehair yarn and woven fabric	3.8**	0.4%
79	Zinc and articles thereof	4.8**	0.1%
35	Albuminoidal substances; modified starches; glues; enzymes	4.1**	0.2%
38	Miscellaneous chemical products	3.3**	1.2%
47	Pulp of wood or of other fibrous cellulosic material; recovered (waste and scrap) paper or paperboard	4.7**	0.3%
15	Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal or vegetable waxes	3.4**	0.6%
24	Tobacco and manufactured tobacco substitutes	5.3*	0.3%
33	Essential oils and resinoids; perfumery, cosmetic or toilet preparations	3.6*	0.7%
61	Articles of apparel and clothing accessories, knitted or crocheted	3.2*	1.6%
13	Lac; gums, resins and other vegetable saps and extracts	4.9*	0.0%
18	Cocoa and cocoa preparations	4.1*	0.3%
36	Explosives; pyrotechnic products; matches; pyrophoric alloys; certain combustible preparations	4.5*	0.0%

*** p-value<0.01, ** <0.05, * <0.1 (statistical test: share of anomalies > 2.5).
§ Percentages refer to the Italy's import and export total values recorded in the COMTRADE database (2010-13)..

5.2 Correlation analysis

In order to test how accurately our risk indicator is actually able to identify illicit commercial transactions, potentially linked to TBML, we have developed a correlation analysis between our country-level risk indicator and some indicators of country opacity or financial attractiveness.

It was previously explained that we explicitly chose not to include such variables in our model for a variety of reasons. Firstly, arguing that any set of indicators, for large as the set may be and for reliable as the indicators could be, could actually account for all rationales that may underlie illegal trade would be a far-fetched act of faith on our side. Secondly, indicators typically suffer from measurement errors or represent rough approximations of any phenomenon they aim to describe and thus risk being held as unreliable. Hence our determination to adopt a 'residual approach', which has been advocated in the previous sections, and turn to indicators somehow related to illegal activities only at the robustness-check stage.

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 believed to be widespread in each. In the following analysis we have considered 2013,[24] 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, an indicator, varying between 0 and 10 (maximum level of risk), 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.[25] The year of reference for this indicator is 2014, which was the only year available covering most countries of our sample.

Finally, we tested the correlation of our risk indicator with the *Business cost of crime and violence Index*,[26] a component of the World Economic Forum's Global Competitiveness Index, aiming to measure the level of country financial and economic attractiveness (the higher the index, the more attractive a country is).

The correlation analysis between our anomaly indicator and the three indices just mentioned relies on both the Pearson and the Spearman rank correlation indices (see Table 6). If we consider the whole group of Italy's commercial partners, the correlations are significantly negative for the first two indicators (CPI and Basel AML). Though counter-intuitive at a first sight, this result should not be surprising if we scrutinise the countries that both indices rank worst more closely. These mainly include low or lower-middle income nations of the Sub-Saharan Africa (Burkina Faso, Burundi, Guinea, Mali, Uganda, Zimbabwe, Cameroon, Kenya, Lesotho, Nigeria, Zambia), Middle East (Yemen, Iran), or Southeast Asia (Nepal, Cambodia). 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.[27]

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. In keeping with this findings, if the analysis is restricted to the countries with the highest anomaly indicator (those in Table 4), which also include some of Italy's main trade partners, we get a positive (and statistically significant) Spearmen correlation, at least with the Basel AML Index. Conversely, looking at the *Business cost of crime and violence Index*, the

[24] 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).

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

[26] 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]*. For further details see http://reports.weforum.org/global-competitiveness-report-2015-2016/.

[27] The countries in the 50 top rakings according to the CPI and the Basel AML Index account for roughly 10% of Italy's external trade.

positive and significant correlation coefficients show that the likelihood of observing anomalous trade flows between Italy and each partner country increases with the level of financial and economic attractiveness.[28]

Table 6.
Correlation between TBML risk indicators and indexes of countries' opacity/financial attractiveness

	Pearson correlation	
	all countries	if anomaly indicator>0.025
	anomaly indicator	anomaly indicator
CPI	-0.350***	0.032
Basel – AML	-0.298***	0.267
Business cost of crime and violence	0.388***	-0.056
	Spearman correlation	
	all countries	if anomaly indicator>0.025
	trade index	trade index
CPI	-0.378***	-0.020
Basel – AML	-0.393***	0.367**
Business cost of crime and violence	0.438***	0.016

These results confirm that trade flow anomalies are likely to be observed not only with countries (at least, apparently) 'less opaque', but also showing higher level of financial attractiveness because economically developed or politically stable. Accordingly, false trade transactions – regardless the way they are finalised – are rarely liable to occur with developing and politically unstable countries, which often feature high level of perceived corruption but also weak financial allure. [29]

6. Concluding remarks

Practitioners in the field of fighting money laundering and financial crime have sounded the alarm on criminals' 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 the illegal financial flows underlying them, which may complement and support the activity by investigative bodies, itself focussed 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.

[28] As opposed to the country-specific indexes, the 50 top countries according to the *Business cost of crime and violence Index* cover nearly 70% of Italy's external trade.
[29] As robustness check, we computed the mean of the CPI and Basel indicators for the 'anomalous' countries listed in Table 4 and found that the values are significantly lower with respect to the mean of 'non-anomalous' countries; exactly the opposite result was obtained for the Business cost of crime and violence indicator (the average indicator for countries in Table 4 is higher than for countries not included in the list), thus supporting the results obtained from the correlation analysis (all the results were attained by mean-comparison tests at a significance level of 1%).

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 and every 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 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) correction of trade data for the usual *cif/fob* discrepancy relies on point estimates for freight costs at an extremely detailed level of accuracy, instead of being carried out across the board by 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 seem to be consistent with the literature and, accordingly with the expected results, in terms of sign and size of the coefficients. Our risk indicators, based on the model's estimated random effects, leads to the compilation of rankings of product-country pairs and consequently to the separate identification of riskier countries and product lines.

Though all rankings seem to be basically consistent with day-to-day experience of practitioners in the field, the robustness and significance of the results, at least with reference to the country risk indicators, is tested against some widely used country's risk measures in terms of perceived corruption, money laundering and economic impact of criminal activities.

The results obtained are mixed, but all seem to point in the same direction: potential TBML may be more largely observed in trade flows *vis-à-vis* countries featuring low levels of risk, with reference to the dimensions measured by the indicators being applied. 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.

The direction our analytical framework can be fruitfully expanded towards follows two main avenue of research.

First and foremostly, the same methodology relying on the analysis of mirrored trade statistics 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 and every 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. In addition, information on single transactions that would include the parties to that 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 of the parties involved.

Both possible further developments would very much mimic the one illustrated in the present study in that both would purportedly lead to the definition of statistic-based analytical tools to be deployed for day-to-day operations and checks by practitioners 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 (HS 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 NST2007product classification, which is converted to HS 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.

References

Ardizzi G., De Franceschis, P. and Giammatteo, M. (2016), *Cash payment anomalies: An econometric analysis of Italian municipalities*. UIF, Quaderni dell'antiriciclaggio, Collana Analisi e Studi, n. 5.

Asia/Pacific Group on Money Laundering (2012), *APG Typology Report on Trade Based Money Laundering* (July).

Bank of Italy (2016), *Italy's international freight transport: 2015*, Rome, October 2016, http://www.bancaditalia.it/statistiche/tematiche/rapporti-estero/trasporti-internazionali/sintesi-indagini/en-indagine-trasporti15.pdf?language_id=1.

Bell A., and K. Jones (2015), *Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data*, Political Science Research and Methods, 3(1), pp. 133-153.

Berger, H. and Nitsch, V. (2012), *Gotcha!: a Profile of Smuggling in International Trade*. In Costa Storti, C. and de Grauwe, P. (eds), *Illicit Trade and the Global Economy*. MIT Press

Bhagwati, J.N. (1981), *Alternative Theories of Illegal Trade: Economic Consequences and Statistical Detection*. Weltwirtschaftliches Archiv, Bd. 117, H. 3, pp. 409-427, Springer.

Buehn, A., and Eichler, S. (2011), *Trade Misinvoicing: The Dark Side of World Trade*. The World Economy, doi: 10.1111/j.1467-9701.2011.01375.x

Cassetta A., Pauselli C., Rizzica L., Tonello M. (2014), "*Financial flows to tax havens: Determinants and anomalies*" *UIF,* Quaderni dell'antiriciclaggio, Collana Analisi e Studi, n. 1.

Carrère, C., and Grigoriou, C. (2014), *Can Mirror Data Help to Capture Informal International Trade?* Policy Issues In International Trade And Commodities Research Study Series No. 65, UNCTAD.

de Boyrie, M.E., Pak, S.J. and Zdanowicz, J.S. (2005), *Estimating the Magnitude of Capital Flight Due to Abnormal Pricing in International Trade: The Russia–USA case.* Accounting Forum 29(3):249-270 (September), doi: 10.1016/j.accfor.2005.03.004.

European Central Bank (2016), *European Union Balance of Payments and International Investment Position Statistical Methods ("B.O.P. and I.I.P. Book"),* Frankfurt, November 2016 edition, https://www.ecb.europa.eu/pub/pdf/other/eubopintiinvposstmeth201611.en.pdf?0504f8e012f05f064a84860c6851c3fe

Federico, G. and Tena, A. (1991), *On the accuracy of foreign trade statistics, 1909–1935: Morgenstern revisited.* Explorations in Economic History, 28, 259–273.

Financial Action Task Force (2006), *Trade Based Money Laundering*, Paris (June).

Fisman, R. and Wei, S.J. (2009), *The Smuggling of Art, and the Art of Smuggling: Uncovering the Illicit Trade in Cultural Property and Antiques*. Applied Economics Vol. 1, No. 3, pp. 82-96 (July).

Ferwerda, J. Kattenberg, M. Chang, H-H Unger, B. Groot, L. Bikker, J.A. (2013), *Gravity models of trade-based money laundering.* Applied Economics, 45:22, pp. 3170-3182, DOI: 10.1080/00036846.2012.699190.

Hamanaka, S. (2012), *Whose Trade Statistics Are Correct? Multiple Mirror Comparison Techniques: a Test Case of Cambodia*. Journal of Economic Policy Reform, Vol. 15, No° 1, 33-56 (March).

Kar, D. and Cartwright-Smith D. (2008), *Illicit Financial Flows From Developing Countries: 2002-2006*. Global Financial Integrity, Washington, DC.

International Monetary Fund (1993), *A Guide to Direction of Trade Statistics*. Washington, DC.

McDonald, D.C. (1985), *Trade Data Discrepancies and the Incentive to Smuggle: An Empirical Analysis*, IMF Staff Papers, Vol. 32, No. 4, pp. 668-692 (December).

Mundlak Y., (1978), *Pooling of Time-series and Cross-section Data*, Econometrica, 46(1), pp. 69-85.

Nitsch, V. (2011), *Trade Mispricing and Illicit flows*. Tecnische Universitat Darmstadt, Discussion Papers in Economics n° 206, http://tuprints.ulb.tu-darmstadt.de/4720/1/ddpie_206.pdf

Nitsch, V. (2016), *Trillion Dollar Estimate: Illicit Financial Flows from Developing Countries*. Tecnische Universitat Darmstadt, Discussion Papers in Economics n° 227, http://tuprints.ulb.tu-darmstadt.de/5437/1/ddpie_227.pdf

Pastori, E., Tagliavia, M., Tosti, E., and Zappa. S. (2014), *L'indagine Sui Costi del Trasporto Internazionale delle Merci in Italia: Metodi e Risultati*. Quaderni di Economia e Finanza della Banca d'Italia, n° 223, http://www.bancaditalia.it/pubblicazioni/qef/2014-0223/index.html.

Patnaik, I, Gupta A.S. and Shah A. (2012), *Determinants of Trade Misinvoicing*. Open Economies Review, vol. 23, issue 5, pages 891–910 (November). Springer. Doi: 10.1007/s11079-011-9214-4.

Pitt, M.M. (1981), *Smuggling and Price Disparity*. Journal of International Economics, vol. 11, issue 4, pages 447-458, Elsevier.

Rabe-Hesketh, S. and Skrondal, A. (2012), *Multilevel and Longitudinal Modeling using Stata*, (Third Edition).

Skrondal A., and S. Rabe-Hesketh (2004), *Generalized Latent Variable Modeling: Multilevel, Longitudinal and Structural Equation Models*, Boca Raton: Chapman and Hall.

Yalta, A.Y. and Demir, I. (2010), *The Extent of Trade Mis-Invoicing in Turkey: Did Post-1990 Policies Matter?*. Journal of Economic Cooperation and Development, January 2010.

Yeats, A. J. (1990), *On the Accuracy of Economic Observations: Do Sub-Saharan Trade Statistics Mean Anything?* World Bank Economic Review 4(2): 135-156.