Presenting a new atlas of illicit financial flows from trade misinvoicing

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November 27, 2022
Latest version

Abstract

Trade misinvoicing is an illicit practice designed to move money in and out of a country through the deliberate falsification of customs invoices at import and export. Existing estimates of trade misinvoicing have typically relied on the simplifying assumption that discrepancies in mirror international trade data over and above costs of insurance and freight represent misinvoicing. We propose an improved methodology that adjusts for many of the other potential sources of 'non-illicit discrepancies' in mirror trade statistics. We present a global dataset of trade misinvoicing estimates for 167 countries for the period 2000-2018. We find that developing countries lost $1.7 trillion in gross illicit outflows during that period, an average of $131 billion a year. Our dataset provides disaggregated estimates of illicit financial flows by sector and country and will allow policy-makers to identify sources, sinks, and sectors to focus their efforts on. We find that the sectors that account for the most misinvoicing are mineral products and machinery and electrical. The top destinations of outflows from developing countries are rich countries and those with high levels of financial secrecy. Trade misinvoicing hampers development by diluting public revenues, undermining tax authorities, weakening governance, and eroding state institutions. Combating trade misinvoicing is crucial for the mobilization of domestic resources and can help catalyze sustainable development.

*Postdoctoral Fellow, Brown University. Corresponding author: alice_lepissier@brown.edu. The methodology section of this paper draws on an unpublished methodological note prepared for the United Nations Economic Commission for Africa (UNECA) by Alice Lépissier. Part of this work was carried out while Alice Lépissier was employed as a consultant for UNECA during portions of 2018 and 2019. Sections 2 and 3 of this paper were written by Alice Lépissier as part of her PhD dissertation and are reproduced with permission. The methodology is developed in the authors' personal capacity and does not necessarily reflect the views of their respective institutions. The authors gratefully acknowledge comments from Simon Mevel, Alex Franks, Robert Heilmayr, Alexey Kravchenko, Matthew Potoski, and workshop participants at the University of California Santa Barbara. All remaining errors and omissions are our own.

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Contents

1 Introduction

Tackling illicit financial flows (IFFs) has become a key international policy priority in recent years. The fight against illicit finance has been the subject of international cooperation efforts at the United Nations, the OECD, and various intergovernmental fora. There is a general recognition that illicit financial flows erode the ability of governments to generate resources and directly undermine the efforts of the global community to successfully achieve the Sustainable Development Goals (SDGs). The United Nations Conference on Trade and Development (UNCTAD) estimates that there is an annual financing gap of $2.5 trillion for developing countries to achieve the Sustainable Development Goals (Doumbia and Lauridsen, 2019). Illicit financial flows create an uneven playing field both domestically by increasing wealth disparities and internationally by threatening the prospects of development for poor countries. Combating IFFs is of primordial concern to developing countries if they are to mobilize domestic resources to finance their own development.

The term illicit financial flows was first coined by Baker (2005) who defines IFFs as the movement of money across borders that is illegally earned, transferred, or utilized. At some point in the origin, destination, or movement of the money, laws were broken and hence the corresponding financial flow is considered illicit (Kar, 2010). Trade misinvoicing is the main source of illicit financial flows (see, e.g., Spanjers and Salomon (2017); Salomon (2019)) and existing estimates have suggested that developing countries lose hundreds of billions of dollars each year through trade misinvoicing (Spanjers and Salomon, 2017), while other literature suggests that such practices are a key weakness in the fight against corruption, transnational organized crime, and the financing of terror (Findley et al., 2020; UNODC, 2011; FATF, 2019).

Measuring and tracking illicit flows is extremely challenging, since by their very nature illicit flows are not systematically recorded. The difficulties of quantification are a significant hindrance to understanding the extent of the problem and where it is most severe. This paper contributes a novel methodology to estimate trade misinvoicing at scale and with sufficient resolution, and offers an "atlas of trade misinvoicing" that contains bilateral estimates of misinvoiced trade for 167 countries during 2000-2018 at a disaggregated sectoral level for all commodities reported to UN Comtrade.

Existing trade misinvoicing estimates have faced intense scrutiny about the robustness of their methodologies; with some authors considering that the methodological flaws of the estimates render them devoid of any substantive meaning (Nitsch, 2016) and some lamenting that the debate on the scale of illicit outflows might be a distraction from the more pressing underlying issues (see, e.g., Reuter (2012)). The methodology in this paper provides improvements that seek to address long-standing concerns in the literature on estimating trade misinvoicing. One of the main criticisms holds that the estimates use discrepancies in mirror trade statistics as a proxy for trade misinvoicing, but that there are many potential "non-illicit" sources for such discrepancies, which may be the cause of most of this apparent trade misinvoicing. The approach presented here allows for a systematic way of adjusting for all important sources of "non-illicit" discrepancies.

The paper proceeds as follows. In order to understand the added value of the methodology, section 2 first presents the main concepts behind trade manipulations and discusses how different channels of misinvoicing are harmful. Section 3 of the paper makes the general case for how and why the "atlas" method offers improvements to mitigate the problems of existing methodologies. Six criteria by which to judge whether an estimate is a credible measure of trade misinvoicing are advanced, that consider both methodological cogency and practicality (section 3.1). The most revelant existing methodologies in the literature are critically appraised in terms of how much they fulfill those criteria (section 3.2). Then, the main innovations of the "atlas" methodology are presented in order to demonstrate that the measure exhibits all the characteristics of a good measure of trade misinvoicing (section 3.3).

Step-by-step details of the methodology are provided in section 4, in addition to further discussions of the assumptions and methodological choices involved. Section 5 presents the main findings and provides a practical application of how the "atlas" can be used to zoom in to different views of the problem. Section 6 discusses the limitations of the approach and section 7 concludes.

2 Channels of trade misinvoicing

Trade misinvoicing is the deliberate mis-statement of invoices presented to customs in order to clandestinely shift money abroad or repatriate money domestically. The stratagem is used for a variety of nefarious purposes including money laundering, tax evasion, and the financing of terrorism. Both imports and exports can be misinvoiced and can result in either an illicit outflow or an illicit inflow. The type of trade manipulation that is used depends on the underlying motives for concealing money transfers, and these in turn will harm the prospects for sustainable development and good governance in a variety of ways. In order to critically appraise a measure of trade misinvoicing, it is necessary to understand the directions of the illicit flows and how misinvoicing manifests in both import and export trade flows. This section presents the four main types of trade manipulations, explains how each channel is exploited for different purposes, and briefly discusses the development impacts of these manipulations.

Trade invoices can be faked by either the importer, the exporter, or both, which gives rise to four types of manipulations that are executed for varied reasons. The type of manipulation depends on the aims of the misinvoicer. Shifting or retaining money abroad can be accomplished by import over-invoicing or export under-invoicing, which result in an illicit outflow where either excessive funds or merchandise leaves the country. This is a type of "technical smuggling" as opposed to the "pure smuggling" that occurs when illegal goods such as drugs are clandestinely traded (Schuster and Davis, 2020). When the value of imports is overstated, excess funds leave the country disguised as a form of trade payment (Schuster and Davis, 2020; World Customs Organization, 2018). When the value of exports is understated, this results in an outflow of merchandise in excess of the foreign exchange that is received in return. Export under-invoicing can be used to conceal profits abroad, since commodities leave the country but the corresponding financial flows stay partly in foreign accounts (Schuster and Davis, 2020), which deprives countries of precious foreign exchange and erodes their tax base.

Import under-invoicing and export over-invoicing, on the other hand, will result in an inflow. The potential to evade tariffs by understating the value of imports has been pointed out since Bhagwati (1964). The conventional wisdom among economists, bolstered by empirical evidence (Sachs and Warner, 1995), is that tariffs usually depress economic growth. The existence of the World Trade Organization (WTO) is predicated on this view, and its stated mandate is to reduce tariffs and other barriers to trade. The WTO aims to prevent "beggar thy neighbor" policies where countries engage in zero-sum mercantilist policies which end up leaving every trading partner worse off. Nevertheless, tariffs can also be seen as protective instruments designed to shore up infant industries, promote import substitution industrialization, or even temper the unequal distribution of gains and losses resulting from trade liberalization (Chang, 2005; Rodrik, 2018). Therefore, tariffs are elements of both a country's trade policy and its foreign policy. Irrespective of their economic desirability, tariffs are tools at the disposal of a sovereign nation. Evading a tariff is illegal and thus weakens the rule of law. Moreover, even though tariff evasion will manifest as an inflow (i.e., import under-invoicing), it effectively robs governments of tax revenues.

In addition, misinvoicing occurs opportunistically to exploit subsidy regimes. Export over-invoicing is used to take advantage of incentives that the government puts in place to encourage exports, such as subsidies or tax credits (Gara et al., 2019). As part of their overall economic strategy, countries sometimes seek to subsidize certain industries. Industries can be subsidized in order to champion certain strategic sectors that are in the national interest, in order to sustain a long-run comparative advantage in international trade, or even to guide a national transition towards a different sectoral make-up of the economy. By opportunistically over-stating the true value of their goods, misinvoicers can take advantage of such subsidy regimes in order to capture rents (Baker et al., 2014). Similarly, taking advantage of export subsidy regimes will look like an inflow, but it is a form of market abuse that can make it more difficult for the state to finance other socially beneficial activities.

More generally, trade misinvoicing is used to hide transfers of capital. Motivations for disguising transfers of capital range from financing terrorism and laundering criminal proceeds to tax evasion by individuals and corporations. For example, organized crime syndicates may use trade misinvoicing to repatriate capital and incorporate the proceeds of crime into the domestic legal financial system (UNODC, 2011). Trade misinvoicing can also be used to conceal transfers of wealth that do not stem from criminal activity. For example, capital that is gainfully earned can be moved out of a country to low-tax jurisdictions in order to avoid tax, or to secrecy jurisdictions in order to escape the rules and regulations of the home country. Multinational corporations frequently use misinvoicing to reduce their domestic tax burden by shifting their profits to a lower-tax jurisdiction (Leblanc, 2014; ECLAC, 2016; Vicard, 2015). Widespread tax avoidance by multinational corporations impacts developing countries more severely than developed countries (UNECA, 2019).

Trade misinvoicing impedes the prospects for sustainable development in developing countries. Illicit financial outflows through trade misinvoicing reduce the level of aggregate demand and result in a reduction of economic output (at least in the short term) (UNCTAD, 2016). Even if the funds end up being “round-tripped” to the country from which they departed, less will return than originally left, due to the portion of the funds that will inevitably be paid to various enablers through the process of round-tripping (UNECA, 2018a). This may be particularly damaging where natural resources owned by the state are being exported: the amount of under-invoicing in such cases represents direct diversion of wealth from the national treasury to whoever collects the benefits of the under-invoicing on the other end of the transaction (UNCTAD, 2016). In addition, by circumventing foreign exchange controls, trade misinvoicing may also undermine national strategies for managing the exchange rate, potentially causing the price of imports to rise or (conversely) lowering export competitiveness, which may have negative consequences depending on the circumstances of the affected country (e.g., Griffiths (2003)).

Trade misinvoicing reduces tax revenues and erodes the tax base (Kar, 2010; Jha and Truong, 2015), which undermines public spending and governance, in turn slowing economic growth and worsening poverty (Ibis Ghana and Africa Centre for Energy Policy, 2015; ACTSA, 2019; Baker et al., 2014; Moore, 2007). While the loss of capital is the most immediate consequence of illicit outflows, the indirect consequences of trade misinvoicing are the erosion of governance and weakening of state institutions. Illicit inflows are detrimental to development since they are untaxed and invisible to governments. Moreover, illicit inflows may themselves be used to fund illicit sectors in the economy through the repatriation of profits by transnational crime organizations or may be used to finance terror (Cobham and Janský, 2020). Therefore, illicit inflows from trade misinvoicing have the potential to be just as corrosive to good governance and state institutions as illicit outflows (Blankenburg and Khan, 2012; Spanjers and Salomon, 2017; Salomon, 2019)

A (perhaps less obvious) impact of trade misinvoicing is on the quality of official statistics. Misinvoicing leads to incorrect recording of the market value of goods and services being traded, which may mislead countries as to the relative value or potential of different industries (ESCWA, 2018), leading to poorer economic policy-making (Jerven, 2013).

Therefore, preventing illicit financial flows from trade misinvoicing is an urgent policy priority, and difficulties in quantifying the phenomenon have slowed progress. This paper contributes a novel approach to estimating trade misinvoicing and offers an "atlas of misinvoicing" – a comprehensive collection of bilateral estimates for country pairs. Understanding the four types of trade manipulations presented above is a prerequisite for generating bilateral estimates. At this stage, it is necessary to distinguish between "reporter" and "partner" countries. Following the practice of "double entry accounting" in the compilation of international trade statistics, every trade transaction is reported twice to the United Nations Commodities Trade (Comtrade) database. A given country i (the "reporter") will report the value of its imports from a foreign country j (the "partner"), and that foreign country will in turn report the value of its exports to i. The exports reported by i's partner j are the "mirror exports". Likewise, country i will also report the value of its exports to its partner j to Comtrade, while the partner j will declare the corresponding "mirror imports" to Comtrade.

The "atlas of misinvoicing" approach always proceeds from the perspective of the reporter i (whether the trade flow reported to Comtrade is imports or exports): trade misinvoicing is estimated both in import and export transactions for *reporters*. In other words, this paper estimates the misinvoicing that is present in the import and export invoices that are presented at country i's customs, not j's. In turn, estimating the misinvoicing for all countries i in the set of reporters will yield the misinvoicing for partners too (since a partner j also reports to Comtrade). More specifically, reporters are the set of countries $\{i, \ldots, n\} \in \mathcal{I}$ that report to Comtrade a trade transaction with a partner j. Since not every country i trades with every other country in the world, the set of possible partner countries is a subset of the reporter set: $\{j, \ldots, k\} \in \mathcal{J} \subset \mathcal{I}$ with $k \leq n$. Therefore, to calculate illicit trade for every country that reports data to Comtrade, the methodology proceeds from the perspective of the reporting country i. Hence, the reporter i is the proverbial "atlas" (the topmost vertebra which supports the backbone) from whose vantage point trade misinvoicing is estimated.

As explained above, trade misinvoicing can result in an inflow or an outflow, and this can be achieved by misreporting the value of imports and/or exports. Figure 1 represents the direction of illicit flows from the perspective of the reporting country i and the associated mechanisms. Money can be moved out of country i by over-invoicing imports, where country i pays too much money to buy goods from its partner j; or by under-invoicing exports, where country i does not charge enough money for the goods that it sells to its partner j. Conversely, money can be illicitly routed from country j into country i by under-invoicing imports, where i pays too little money to buy goods from its partner j; or by over-invoicing exports, where i charges too much for the goods that it sells to its partner j. The direction of illicit flows from the perspective of the reporting country and the associated mechanisms is represented in the stylized figure 1 below.

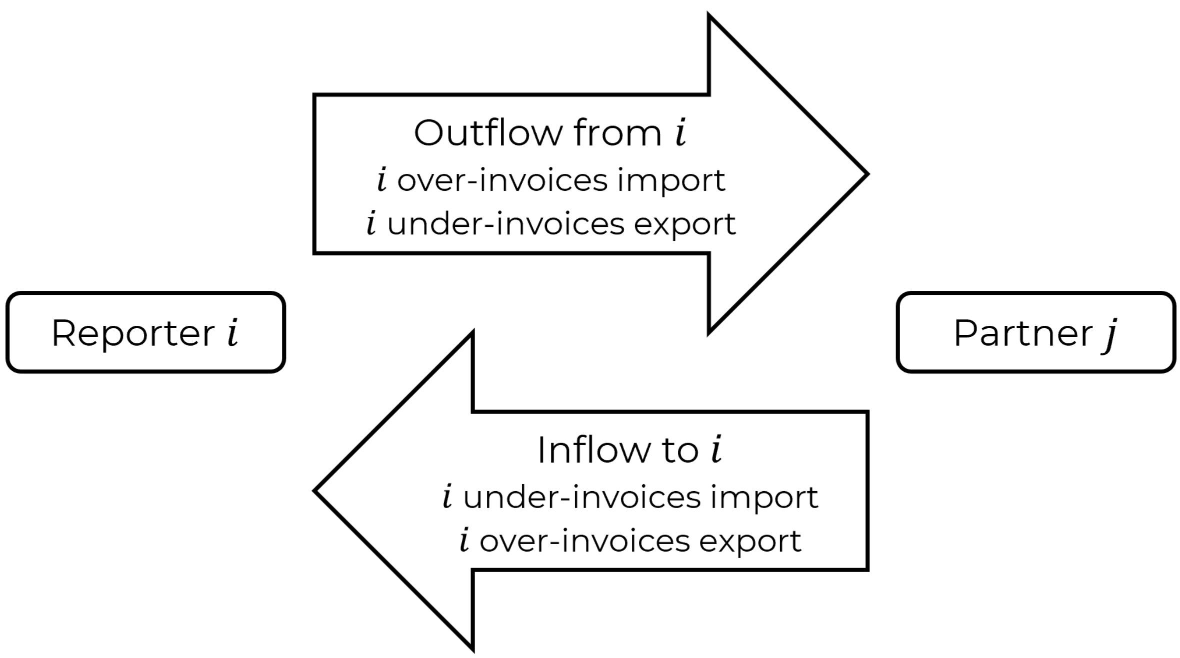

Figure 1: Mechanisms of trade misinvoicing from the perspective of the reporter.

With the requisite preliminaries out of the way, section 3 now sets out to explain how to measure trade misinvoicing by proposing a set of desirable features that a measure should possess in order to convincingly address the key methodological critiques in the literature.

3 Measuring trade misinvoicing

Policy-relevant estimates of illicit financial flows should serve two main functions: first, to highlight the extent of the problem so that countries can decide to what extent to prioritize policy action; and second, to indicate where the problem is worse and where attention should be focused to counter it, by indicating the main channels through which illicit finance is routed, and the main destinations at which it arrives.

The credibility of existing estimates of trade misinvoicing has been hotly contested, and the usefulness of existing estimates in informing policy interventions against IFFs is the subject of ongoing debates (see, e.g., Nitsch (2012, 2016); Cobham and Janský (2020); Picard (2003)). Some authors have highlighted their value in drawing attention to the scale of the problem and galvanizing much needed policy action to combat trade misinvoicing (UNECA, 2018a; Spanjers and Salomon, 2017; Salomon, 2019), while others have dismissed trade misinvoicing as an irrelevant sideshow whose importance has been vastly overstated as a result of the poor methodologies used in attempts to estimate it (Nitsch, 2016; Forstater, 2016). For this reason, developing a robust measure of trade misinvoicing is not only important to advance scholarship on IFFs, but it is also an urgent policy priority in order to justify reforms.

The definitional and methodological debates that have raged in the literature on IFFs are reflected politically by the lack of agreement by the United Nations member states on a comprehensive measure of illicit financial flows. Though the global community has recognized the importance of combating illicit finance by enshrining it as a Sustainable Development Goal (SDG), there is no concensus on how to evaluate progress towards that goal. Goal 16.4 of the SDGs aims to "by 2030, significantly reduce illicit financial flows and arms flows, strengthen the recovery and return of stolen assets and combat all forms of organized crime" (UN General Assembly, 2015) without specifying what constitutes a reduction of IFFs, let alone what the baseline measure is.

The development of common frameworks and indicators for measuring progress towards the SDGs has been the subject of international cooperation at the highest political levels. The consortium of governments and intergovernmental organizations tasked with developing a statistical framework for the SDGs initially ranked the indicator of IFFs at the lowest possible level, meaning that there was no internationally established methodology or standard for measurement, compared to other SDGs that have well-defined indicators for measuring progress.[1] Policy work is ongoing to clarify the subcategories of IFFs that will be included in the indicator and how they can be measured at a disaggregated level (see UNODC and UNCTAD (2020)). Therefore, the development and creation of policy-relevant proxy indicators of IFFs by researchers is a timely and valuable endeavor.

This paper contributes a novel indicator of trade misinvoicing (a subset of the IFF target) that offers broad country coverage *and* disaggregated estimates at the same time. To my knowledge, there are no existing estimates of misinvoicing that do so at a global scale. The "atlas of trade misinvoicing" provides measures of illicit trade for 167 countries during 2000-2018 for all commodities reported in Comtrade, disaggregated by 99 commodity sectors. This measurement of trade misinvoicing has already been used by international organizations,[2] notably to motivate a pilot initiative to strengthen customs system in selected African countries,[3] which bolsters the value of this database for providing tailored intelligence to decision-makers working on IFFs.

In this section, I first develop the properties that a credible measure of trade misinvoicing should possess, then evaluate the extent to which current methodologies satisfy those criteria, and finally I show how the estimation strategy of the "atlas of misinvoicing" meets these criteria and mitigates long-standing problems in the literature and demonstrates both methodological rigor and applicability in practice.

[1] In 2015 the United Nations Statistical Commission created the Inter-agency and Expert Group on SDG Indicators (IAEG-SDGs) and tasked it with developing and implementing the global indicator framework for the targets of the 2030 Agenda. The IAEG-SDGs is composed of UN Member States and includes regional and international agencies as observers. The conceptual statistical framework for illicit financial flows measurement was initially classified under tier 3 of the SDGs global indicators. It was only in October 2019 that the IAEG-SDGs endorsed a reclassification of the indicator to tier 2, meaning that the indicator is conceptually clear, has an internationally established methodology and standards are available, but data are not regularly produced by countries.

[2] Results based on an earlier iteration of this methodology were used as the United Nations Economic Commission for Africa (UNECA) estimates of illicit financial flows from Africa. UNECA was represented in a series of expert meetings on statistical methodologies for measuring illicit financial flows, as part of the multilateral push to develop indicators for the IFF target of the SDGs. Further, results were also included in the *Financing for Sustainable Development Report 2019* of United Nations Inter-agency Task Force on Financing for Development (2019), available at https://developmentfinance.un.org/sites/developmentfinance.un.org/files/FSDR2019.pdf.

[3] UNECA works with African countries to scale up domestic resource mobilization and implement policy interventions against IFFs at the national government level. Early results of the "atlas" measure were used to inform a pilot project in six African countries that focused on building the capacity of national customs authorities and Financial Intelligence Units to detect and control trade misinvoicing. The measure was used to identify the key sectors, sources, and sinks of misinvoiced trade in Egypt, Nigeria, Senegal, South Africa, Tunisia and the United Republic of Tanzania, and to provide operational insights for these countries' customs administrations. For more information, see https://repository.uneca.org/handle/10855/43054.

3.1 Properties of a good measure of trade misinvoicing

There exist certain criteria that a measure of trade misinvoicing should meet in order to deliver estimates that are both theoretically cogent and practically meaningful. I submit the following set of six desirable properties for candidate measures of trade misinvoicing.

1. Avoid uncritically equating observed trade irregularities with misinvoicing
2. Partition the trade transaction into licit and illicit components in order to account for persistent non-illicit reasons for discrepancies
3. Account for the variance in countries' statistical reporting
4. Scale across jurisdictions and over time
5. Provide enough granularity to support policy prioritization
6. Use open government data

The first three properties are concerned with the integrity of the methodological construct, while the final three characteristics are desirable in order to generate meaningful insights for researchers and practitioners.

Criterion 1. ***Avoid uncritically equating observed trade irregularities with misinvoicing.***

Irregularities in trade statistics do not necessarily imply foul play. Although irregularities might be indicative of misinvoicing in some cases, it would be incorrect to deduce that they are necessarily due to deliberate trade misinvoicing. Conversely, the *absence* of irregularities does not imply an absence of misinvoicing (World Customs Organization, 2018; Nitsch, 2012).

The following examples illustrate both types of logistal mistakes. There have been several cases of highly publicized estimates of lost revenues for African governments in the mineral sector that were later revealed to be "false positives", and as a result were publicly rebuffed and gave way to sweeping retractions. Instead of representing widespread theft of assets and rampant smuggling, the anomalies identified by these estimates could be attributed to readily explainable facts such as re-exporting and differences in reporting procedures. A prominent report by the United Nations Conference on Trade and Development (UNCTAD, 2016) suggested that up to 67% of gold exports from South Africa left the country unrecorded and that the country lost $78 billion dollars in IFFs during 2000-2014. The South African Revenue Service and the South African Chamber of Mines strongly objected to these findings, and argued that the mismatch between South Africa's records of gold exports and the import declarations of its trade partners was due to the peculiarities of South Africa's reporting practices, rather than egregious misappropriation of export revenues by mining companies.[4] In particular, South Africa has a special trade regime for gold where (a) before 2011, gold exports were not recorded as a commodity to Comtrade but rather as a monetary flow in the IMF's Balance Of Payments, and (b) after 2011, even though gold exports were reported to Comtrade, they were not broken down by destination; both of which introduced spurious discrepancies in trade statistics (Schuster and Davis, 2020; Van Rensburg, 2016; Eunomix Research, 2017).

The other notable "false positive" case was that of Zambian copper and Switzerland. Zambia is a major copper producer and declares that more than 50% of its copper exports are destined for Switzerland (Schuster and Davis, 2020). By contrast, Switzerland reports no imports of copper from Zambia, but declares high export values of copper to third countries. The resulting trade gaps were used to make a – now retracted – claim that, if Zambia received the same export prices for copper as had been declared on Swiss exports, then Zambia's GDP in 2008 would have been 80 percent larger.[5] However, Switzerland is a major trading hub and the observed trade discrepancies are likely due to merchanting, whereby a Swiss company buys copper from a Zambian company, but stores the copper in bonded warehouses on the London Metal Exchange before reselling it to a final destination, without the copper ever entering Switzerland (Schuster and Davis, 2020). Therefore, usual practices in international commodity markets such as re-exporting can create illusions of IFFs due to asymmetric reporting.

While the two above examples are cautionary tales about the dangers of "false positives", there is also a risk of "false negatives". The absence of trade irregularities cannot be taken as evidence that there is no misinvoicing (Hong and Pak, 2017). One reason for this is if the importer and the exporter collude at both ends of the transaction to present inflated invoices to customs, a phenomenon called "same invoice faking", then the trade records will match even though they are falsified (Kar, 2010; World Customs Organization, 2018). Therefore, inferring that a particular transaction has not been misinvoiced from the absence of discrepancies in records is a logical fallacy that appeals to ignorance as the main premise for the argument. The silver lining is that, since strategies that exploit bilateral trade gaps to produce IFF estimates (an approach that this paper also adopts) cannot account for all

[4] See the press statement that was immediately issued by the South African Revenue Service (SARS) disputing the claims (South African Revenue Service, 2016), a report commissioned by the Chamber of Mines which lambasted the methodology of the UNCTAD report (Eunomix Research, 2017), and critical coverage in the South African media (Van Rensburg, 2016).

[5] See the original claim by Cobham et al. (2014) and the subsequent retraction at `https://cgdev.org/blog/how-much-are-developing-countries-losing-commodity-mispricing-really`.

instances of misinvoicing, they are conservative as a result. Therefore, estimates should be interpreted as a lower-bound of the true extent of the phenomenon.

In practice, however, all methods that estimate trade misinvoicing from reported data[6] exploit asymmetries and/or discrepancies in the data as an entry point to identifying illicit trade transactions. This leads to the second desirable property.

Criterion 2. ***Partition the trade transaction into licit and illicit components in order to account for persistent non-illicit reasons for discrepancies.***

In order to avoid equating all observed discrepancies with misinvoicing, it is necessary to account for persistent non-illicit reasons for discrepancies, such as honest reporting mistakes. In turn, this requires a strategy to plausibly partition a given trade transaction into its respective licit and illicit components.

There are legitimate reasons why imports and the corresponding mirror export values should differ. The most evident reason is that imports tend to be reported on a Cost of Insurance and Freight (CIF) basis, while exports tend to be recorded Free-On-Board (FOB), so reported import values are often inflated with transport and other transaction costs (World Customs Organization, 2018).

Other non-illicit reasons for discrepancies in records include: a delay between the recording of an import at time t and the recording of the corresponding export in the next time period $t + 1$; asymmetric reporting of re-exports which will introduce artificial discrepancies in bilateral trade statistics; and idiosyncrasies in each country's quality of declaration.

Therefore, a good measure of misinvoicing should have a strategy to account for benign discrepancies in order to generate credible estimates of illicit trade.

Criterion 3. ***Account for the variance in countries' statistical reporting.***

The quality of official statistics varies with the level of economic development of countries (Jerven, 2013). The reliability of a country's declaration to UN Comtrade will be also be a function of its bureaucratic capacity and the robustness of its statistical reporting procedures (Devarajan, 2013; Jerven, 2009; Jerven and Johnston, 2015). The uncritical use of trade

[6] As opposed to cases where misinvoicing is identified in a live setting during inspection of shipments by customs. Note that the measures that this paper is concerned with are not designed to be used for law enforcement purposes. Measures based on aggregate economic and financial data are used for *retrospective* studies rather than *prospective* applications.

data should be avoided as estimates of misinvoicing might instead pick up statistical noise generated by shaky statistics rather than signals of deliberate trade falsification.

Likewise, though there are efforts at standardizing reporting practices, countries sometimes implement different rules for reporting, notably on rules of origin to determine the "economic nationality" of a tradeable product.

Yet, in order to create a measure of trade misinvoicing that is scaleable across jurisdictions, making manual adjustments to a country's reported trade in order to correct for declaration quality and country-specific idiosyncrasies is not practical. Therefore, a systematic approach to adjusting for the variance in bilateral trade declarations is needed.

Criterion 4. ***Scale across countries and over time.***

Relatedly, a desirable charasteric for a policy-relevant measure of trade misinvoicing is that it should scale across countries in order to provide the broadest country coverage possible. While micro-level measures can allow a customs official or auditor to conduct forensic investigations into whether a particular transaction is mispriced, the requisite particulars of the case will impede generalization. For example, cross-checking a trader's name from a blacklist of known financiers of terrorism can help in tracking and dismantling a particular plot, but it will not capture all other instances of misinvoicing. By contrast, macro-level measures of misinvoicing can help identify general trends and patterns and can provide analytical leverage to understand the dynamics of the phenomenon through time.

Note that the data requirements to provide a time series of estimates are particularly onerous and require that the trade statistics used as an input to the model are comparable through time. Moreover, estimating trade misinvoicing over time relies on the assumption that time-specific shocks do not affect IFFs; or at least on an empirical strategy to make this assumption plausible.

Criterion 5. ***Provide enough granularity to support policy prioritization.***

While a useful measure of trade misinvoicing will be scaleable across jurisdictions and over time, the possibility to zoom in with some degree of precision is also valuable. There is a trade-off between the coverage and the resolution of trade misinvoicing measures Cobham and Janský (2020). Measures that scale easily and have broad coverage (macro measures) will necessarily have lower resolution and offer less details on the particulars of a case. What is needed is a meso-level measure that provides the analytical traction of macro-level measures for understanding patterns with the flexibility afforded by micro-level measures for identifying heterogeneity. A meso-level measure can illuminate specific countries that act as conduits and sinks of illicit flows and how these vary across sectors.

Detailed case studies can be used to understand the specific purposes that trade misinvoicing is used for and the conditions that facilitate the shifting of illicit financial flows. However, these case studies rely on expert knowledge and presuppose knowledge by policy-makers of the existence of the problem. For example, the under-invoicing of exports from Uganda to the United Arab Emirates (UAE) has been attributed to Ugandan companies smuggling gold from conflict regions in the Democratic Republic of Congo (Schuster and Davis, 2020). A 2005 UN Security Council resolution imposed sanctions on gold trade with certain regions of the Democratic Republic of Congo (DRC), notably the Ituri region, to stem the financing of arms for militia and para-military groups. Yet it has been established that large gold trading companies in Uganda (Machanga Ltd and Uganda Commercial Impex) were buying gold from Ituri-based non-state armed groups (Schuster and Davis, 2020). The DRC has not reported export statistics since 1986, while in recent years exports of gold from Uganda have significantly increased despite the country's modest gold reserves. Likewise, the exports of gold that Uganda reports to the UAE are much smaller than what the UAE report to be importing from Uganda. Documented cases of gold that is smuggled from the DRC to Uganda and which is then exported to the UAE have allowed analysts to infer that gold exports from Uganda are under-invoiced in order to disguise illicit capital flight out of the country (Lewis et al., 2019; Schuster and Davis, 2020).

However, these case studies are highly specific and require *ex ante* knowledge of the potential risks of illicit trade. A more systematic approach to identifying which cases to investigate further would be valuable. Thus, meso-level measures can shed light on previously overlooked combinations of trading partners and commodity sectors that merit further investigation, and that might benefit from detailed case studies as a folow-up.

Criterion 6. *Use open government data.*

A pre-condition for generating a measure that is practically useful is that it can be estimated with open data, to the extent that this is possible. By open data, I refer to data that adheres (as much as possible) to the principles of "open government data".[7] "Open" government data is an ideal-type that espouses a set of eight aspirational properties for data: complete,

[7]The growing movement of "open government data" aims to increase the accountability of governments to their citizens through greater transparency. See, e.g., the Open Government Partnership: `https://www.opengovpartnership.org/`.

primary, timely, accessible, machine processable, non-discriminatory (i.e., available to anyone with no requirement of registration), non-proprietary (i.e., available in a format over which no entity has exclusive control), and license free (Tauberer, 2014).

Of course, rare are the datasets that evince all these qualities, but this standard provides a useful benchmark that can be used to compare how far away data used to estimate trade misinvoicing is from this ideal standard. For example, a measure that relies on detailed commodity pricing data compiled by an industry organization and that can only be accessed under restrictive conditions would be, according to this criterion, a relatively worse measure than a measure that uses government statistics compiled by National Statistical Offices and that can be exploited, with some transaction costs, by researchers.[8]

To summarize, a credible and policy-relevant measure of trade misinvoicing should meet standards of methodological consistency and of practical validity. The first three criteria proposed above are necessary to ensure that a measure of misinvoicing is approximately unbiased and consistent. The last three criteria are pre-requisites for generating a practical measure of trade misinvoicing that has sufficient reach and can be robustly and transparently replicated. This paper now proceeds to first evaluate how extant measures of misinvoicing score on these criteria, and then demonstrates how the "atlas of misinvoicing" measure is a methodological improvement that meets these criteria.

3.2 Existing approaches to measuring trade misinvoicing

Several methods attempt to estimate the scale of illicit financial flows, including the proceeds from illegal markets, international corporate tax avoidance, and the amount of capital and wealth held offshore (Cobham and Janský, 2020). Here I focus on reviewing approaches to measuring IFFs that occur in the international trade system only. Existing strategies to estimate misinvoicing in trade can be categorized as looking for anomalies in either transactions, prices, or country-level trade statistics (Cobham and Janský, 2020). This section critically evaluates the extent to which these methods generate estimates that meet the six criteria of a credible measure of misinvoicing. Table 1 synthesizes the salient features of the three approaches that are the closest relatives of the methodology introduced by this paper, and appraises how well they perform along the requisite analytical dimensions.

[8]More precisely, the example measure that I give will be a worse measure according to this criterion while *holding the other criteria constant*. I do not attempt to solve the optimization problem of maximizing the performance of a measure across all six dimensions, nor do I propose relative weights that should be placed on these characteristics. The paper does not suggest an index-like scoring of the validity of trade misinvoicing measures. Instead, these criteria should be interpreted as heuristics.

First, there exists a category of misinvoicing measures that operate on the transaction-level, contrary to the country-level estimates that are the focus of this paper. Measures that use transaction-level trade data provide evidence of misinvoicing by looking for systematic differences in the reported prices for goods traded between related parties and those traded between unrelated parties (see, e.g., Vicard (2015); Davies et al. (2018)). These approaches are powerful for estimating transfer mispricing within multinational groups but they are less useful for the other types of trade misinvoicing discussed in section 2. In addition, it would be highly challenging to obtain the data needed to apply this approach to a broad range of countries and so these measures fare poorly on criteria 4 and 6. These approaches are not discussed further since the nature of the data they use (viz., micro-level data on individual transactions) is different from the measures that leverage country-level trade data.[9] Since the ambition of these measures is conceptually different, i.e., they have different estimands, these approaches are not included in the synthesis table 1.

The next category of misinvoicing measures are price-based approaches that look for irregularities in the pattern of prices to detect evidence of illicit financial flows (see, e.g., Hong et al. (2014); Hong and Pak (2017)). The price-filter method calculates per-unit prices for internationally-traded goods and assumes that prices outside a certain range are anomalous, and hence labels the corresponding transaction as an illicit flow, e.g., prices that deviate from the inter-quartile range of the distribution of prices (Zdanowicz, 2004), or prices that are 50% above or below the average price in that country (Zdanowicz, 2009). Building on an example from Zdanowicz (2009), a terrorist wishing to launder \$1 million dollars to a foreign country might purchase 10,000 razor blades domestically for 10 cents a piece, export these to a colluding importer in a different country at \$100 per razor blade, and thus succeed in moving \$1 million to the foreign country less the \$1,000 transaction cost of the razor blade. To detect that this is an illicit flow, the estimation technique rests on recognizing that \$100 per razor blade is an anomalous price by comparing it to the distribution of prices in that product category. Implicitly, this requires a counterfactual of what the normal price of an arms' length transaction should be (Cobham and Janský, 2020); this information is often unknown.

Consequently, the price-filter method has been criticized for the use of arbitrary thresholds to identify outlier prices and the lack of robustness of the estimates (Nitsch, 2012; Cobham and Janský, 2020; Collin, 2019). While this method has the advantage of meeting criterion 5 of a good measure of misinvoicing because it uses micro-level data that is disaggregated by product category, it struggles to meet the remaining criteria. Observing an aberrant price

[9] For a critical review, see Cobham and Janský (2020).

in the price data could be explained by non-illicit reasons (failing criterion 1), such as the export of a high-quality good in a product category that usually trades in cheap low-value merchandise (Nitsch, 2012). This method provides no systematic way to deal with "benign outliers" and so does not meet criterion 2. Compounding this difficulty, estimates derived from this method have been shown to be sensitive to the inclusion of new data (Nitsch, 2012) and increasing with the price variance of the product category (Collin, 2019), and so this method contradicts the principle of criterion 3.

The practical applications of this method also have some limitations. When the price-filter method is applied to advanced economies, researchers are often able to access detailed trade data that is compiled by a government agency, such as data from the United States Merchandise Trade database from the Department of Commerce's census bureau (see, e.g., De Boyrie et al. (2005)). However, countries with less bureaucratic power might not compile such data or make them easily accessible, and so performance on criterion 6 will be mixed. As a result of the data requirements of the price-filter method, these estimates do not scale easily, and are often provided for a single country's illicit trade with one or more partners, thus scoring poorly on criterion 4.

The next category is the class of estimates that leverage country-level statistics of international trade data (which may be aggregated at the commodity-level or not)[10] – the "atlas" measure falls under this category. Extant country-level estimates can be traced back to two historical approaches: the IMF Direction of Trade Statistics (DOTS)-based method and the UN Comtrade method. Both use bilateral or multilateral mismatches in recorded trade flows to measure trade misinvoicing, but differ in the data source that they employ. The approaches are distinguished by the data they use because this coincides with an inflection point in the literature on estimating trade-based IFFs. The data sources broadly represent a first generation (DOTS-based) and a second generation (Comtrade-based) of estimates.[11] Both methods look for "trade gaps" in the data to detect illicit activity, but with varying degrees of sophistication.

The first generation of this type of misinvoicing estimates were pioneered by the think tank Global Financial Integrity (GFI, see, e.g., Kar and Cartwright-Smith (2008) and Spanjers and Salomon (2017)) and were based on the IMF's DOTS database. The DOTS-based approach

[10]Other approaches to estimate IFFs using country-level statistics use errors and omissions in official Balance Of Payment statistics as a proxy for illicit flows. However, these estimates are concerned with capital flight rather than trade-based misinvoicing. Thus, they cannot provide disaggregated estimates of trade misinvoicing by commodity sector. They are not discussed further.

[11]This categorization is imperfect, as the methods sometimes overlap. Moreover, the estimates by Salomon (2019) use both DOTS and Comtrade data.

leverages asymmetries in the bilateral DOTS data to provide evidence of misinvoicing. As discussed in section 2, country-level trade statistics should be recorded twice: once by the reporter i and once by the partner j.[12] Thus, the method compares mirror trade statistics, that is, it compares country i's records of exports to country j with j's reported imports from i in the same year (and *vice versa*), to look for irregularities.

Criterion 2 requires a measure to account for persistent non-illicit reasons for discrepancies, since there are predictable reasons for why an import value is expected to differ from its corresponding mirror export value. The most obvious reason is that records of import values usually include the Cost of Insurance and Freight (hereafter called "CIF" rate or cost) while recorded export values do not. The DOTS-based method adjusts trade gaps for CIF costs but otherwise uncritically equates the CIF-adjusted trade gaps with misinvoicing and risks flagging false positives. As a result, the method has been widely criticized for estimating instances of phantom illicit financial flows and producing results that have no substantive meaning (Nitsch, 2016; Forstater, 2016); it thus fares poorly on 1.

Moreover, the CIF rate has been assumed to be 1.1 by convention which sets the cost of insurance and freight at the constant value of 10%.[13] Treating the CIF costs as constant is a strong assumption that is often not realistic in practice. There are other benign reasons for which mirror trade statistics may not match aside from the cost of insurance and freight, such as asymmetric reporting of re-exports. When goods are re-exported, it is often the case that the re-exporting country will report a time lag in the arrival of shipments (those that are exported in year t and arrive in year $t + 1$).[14] The first generation of DOTS-based misinvoicing estimates adjust for this but through a manual coding procedure that tries to account for all *known* country data idiosyncracies, such as not counting re-exports from known trading hubs such as Hong Kong as misinvoicing (Spanjers and Salomon, 2017). Therefore, the manual and unsystematic strategies employed to adjust for known non-illicit factors in trade gaps imply that the DOTS-based method only partly satisfies criterion 2.

Another major shortcoming of the first generation DOTS-based method is that it often implicitly treats trade declarations by advanced economies as relatively accurate and consequently assumes that the misinvoicing must have happened in the declarations of developing countries (e.g., Ndikumana and Boyce (2010)). The method has been faulted for its un-

[12]In practice, data will sometimes contain "orphaned" transactions.

[13]Salomon (2019) revises the assumption from 10% to 6%, but this does not change the tenor of critique: CIF costs are still assumed to be constant.

[14]However, as noted in UNCTAD (2016), discrepancies due to asymmetric reporting of re-exports are eliminated when trade misinvoicing is aggregated at national level on a net basis (i.e., illicit outflows net of inflows).

critical use of developed countries' trade statistics, without pausing to consider whether those statistics are accurately collected (Mevel et al., 2013). Similarly, the calculation of the total amount of misinvoicing in developing countries with the rest of the world is done through simple extrapolation, which does not account for the possibility of varying levels of misinvoicing and declaration quality across countries. Therefore, criterion 3 is not met.

Finally, in terms of practical applications, the IMF's DOTS database meets all of the criteria of open data standards (criterion 6). The DOTS database is also valued because it has superior country coverage than UN Comtrade (criterion 4) according to Cobham and Janský (2020), though the country coverage of Comtrade is by no means negligible. The limitation of DOTS compared to Comtrade, however, is that it does not provide disaggregated statistics for commodities, thereby limiting its usefulness for sectoral targeting of IFF interventions (criterion 5).

Recognizing the limitations of the DOTS-based approach, the second generation of misinvoicing methods turns to UN Comtrade for more granular estimates, and employs more sophisticated adjustment techniques. This method ("the UN Comtrade method") is used by several United Nations bodies[15] and is used in updated GFI estimates (e.g., Salomon (2019)). Similarly to the DOTS-based method, it employs trade gaps analysis but on trade data that is disaggregated by commodity. Moreover, studies in this category recognize that the cost of insurance and freight will vary by commodity and country pair, and so CIF costs are estimated using data rather than assumed to be constant.[16] The estimates of the CIF margin are based on a gravity-type model of trade costs that takes into account distance between countries and barriers to trade.

Some versions of the UN Comtrade method also adjust for differences in the quality of statistical reporting by using the variance of different partners' reporting to attribute how much misinvoicing occurs at each end (export or import) of the transaction (Mevel et al., 2013). The goal of this econometric adjustment is to eliminate phantom discrepancies that are in fact the result of poor statistical practices in countries' customs (Kravchenko, 2018). Moreover, some studies seek to account for non-illicit reasons for trade gaps by using data on the quantities (rather than the prices) of the commodities being traded. ECLAC (2016); Kravchenko (2018); Salomon (2019) downweigh observations where there is a discrepancy in the reported weight being traded, in order to reduce the impact of instances where the discrepancy is due to either statistical errors, asymmetric reporting of re-exports, or delays

[15] See, e.g., ECLAC (2016); ESCWA (2018); High Level Panel on Illicit Financial Flows from Africa (2015); Kravchenko (2018); Mevel et al. (2013); Schuster and Davis (2020).

[16] One exception is UNCTAD (2016) that uses Comtrade data but still assumes the CIF rate to be constant.

in the arrival of shipments. Therefore, the UN Comtrade studies aim to provide an empirical and data-driven way to account for the benign components of the transaction and to adjust for idiosyncracies in the trade declarations, and broadly meet criteria 2 and 3, respectively.

These studies offer improvements from the DOTS-based analyses, but suffer from limitations that preclude their ability to meet criterion 1 whereby trade irregularities (even if netted of CIF) should not necessarily be attributed to misinvoicing. Since the models used to estimate costs of insurance and freight do not factor in the possibility of trade misinvoicing, their estimates of the CIF margin may be picking up trade misinvoicing (Gaulier and Zignago, 2010). Where studies use reported data on the costs of insurance and freight instead of estimates, these data also face challenges because the reported data themselves may be distorted by misinvoicing to avoid detection (moreover, the data are only available for a few countries – see Miao and Fortanier (2017) – and for the single year 2016).[17] One notable exception is the "residual approach" of Gara et al. (2019), who seek to address this issue by estimating a model of trade discrepancies that controls for the main legal determinants of gaps, and then use the residuals from this regression as proxies for the illicit component of such discrepancies. Therefore, Gara et al. (2019) explicitly aim to control for the licit components of a transaction (criterion 2) and employ an estimation strategy geared towards addressing the requirements of criterion 1.

The use of UN Comtrade has shown promise in terms of practical applications. The UN Comtrade database broadly accords with the principles of open government data (criterion 6). The coverage of the database starts from 1961 to the present, though not all countries report trade values in every year; overall, the coverage of Comtrade is good (Cobham and Janský, 2020). The widespread availability of the data and the standardized estimation techniques of the method would make it easier to provide trade misinvoicing estimates on a large scale (criterion 4). In practice, however, many of the studies tend to concentrate on specific geographical regions and do not provide global estimates (see, e.g., ECLAC (2016); ESCWA (2018)). Similarly, the disaggregated commodity data provided by Comtrade have the potential to generate detailed estimates of trade misinvoicing disaggregated by sector, which provide high value added for policy-makers and can help target interventions. Though there are studies that zoom in to specific sectors (e.g., extractives in Africa (UNCTAD, 2016) or cultural property in the US (Fisman and Wei, 2009)), the full potential of the Comtrade database has yet to be realized, and the performance on criterion 5 stands to be improved.

[17]See https://unctad.org/news/why-and-how-measure-international-transport-costs.

	Method to estimate misinvoicing from trade data		
	Price-filter	**DOTS-based (1st generation)**	**UN Comtrade (2nd generation)**
1	*Poor*. Equates transactions where the price is outside an arbitrary distributional threshold with misinvoicing. No counterfactual for a "normal" price.	*Poor*. Equates CIF-adjusted trade gaps to misinvoicing.	*Poor*. Some equate CIF-adjusted trade gaps to misinvoicing.[18] *Good*. Some use regression residuals to identify misinvoicing.[19]
2	*Poor*. No way to distinguish between outlier prices that are benign or illicit.	*Mixed*. Adjusts for CIF costs but assumes they are constant. Adjusts for re-exporting but manually.	*Mixed*. Some adjust for CIF costs but assume they are constant.[20] Some adjust for re-exporting but manually. *Good*. Some estimate rather than assume CIF costs.[21] Some econometrically isolate legal determinants.[22]
3	*Poor*. Measure is sensitive to sample size and variance of the product-category data.	*Poor*. Assumes that advanced economies report accurately and that the misinvoiced declaration are by developing countries.	*Good*. Some adjust for variance of quality in statistical reporting.[23] Some adjust for discrepancies in reported quantities.[24]

Table continued on next page

[18] UNCTAD (2016); Schuster and Davis (2020).
[19] Gara et al. (2019).
[20] UNCTAD (2016); Salomon (2019).
[21] ECLAC (2016).
[22] Gara et al. (2019).
[23] Mevel et al. (2013); Kravchenko (2018)
[24] ECLAC (2016); Kravchenko (2018); Salomon (2019).

	Method to estimate misinvoicing from trade data		
	Price-filter	**DOTS-based (1st generation)**	**UN Comtrade (2nd generation)**
4	*Poor.* Coverage often limited to a single or a group of countries.	*Good.* Better country coverage than Comtrade.	*Good.* Broad country coverage (>100).
5	*Good.* Provides detailed estimates within disaggregated product categories. Useful for audit purposes.	*Poor.* No disaggregation by commodity. Bilateral estimates only.	*Mixed.* Some provide detailed commodity results but only for certain regions or countries.[25]
6	*Mixed.* Some governments compile detailed transaction-level statistics (e.g., US Census Bureau) but this does not apply generally.	*Good.* IMF DOTS database is open data.	*Good.* UN Comtrade database is open data.
E.g.	De Boyrie et al. (2005); Hong et al. (2014); Hong and Pak (2017)	Ndikumana and Boyce (2010, 2018); Early GFI estimates (Kar and Cartwright-Smith, 2008; Spanjers and Salomon, 2017)	Fisman and Wei (2009); Later GFI estimates use DOTS and Comtrade (Salomon, 2019); UN regional commissions (ECLAC, 2016; ESCWA, 2018; High Level Panel on Illicit Financial Flows from Africa, 2015; Kravchenko, 2018; Mevel et al., 2013; Schuster and Davis, 2020)

Table 1: Appraisal of existing trade misinvoicing measures with respect to the 6 desired properties.

3.3 Features of the "atlas" measure

This section presents the main features of the "atlas" measure and demonstrates how they meet the criteria of a credible measure of trade misinvoicing. First, an abridged summary of the methodology is provided, and then the major methodological improvements of the approach are highlighted. The detailed steps to reproduce the measure are given in section

4.

The strategy exploits the principle of double-entry accounting in international trade statistics to identify illicit trade gaps, an approach that has an extensive history in development economics (see Morgenstern (1950); Bhagwati (1964); Morgenstern (1974)). The methodology is most similar to the UN Comtrade method described above, but offers several refinements. A bilateral trade transaction is recorded twice in UN Comtrade: once from the perspective of reporter i who declares the value of imports (exports) from its partner j, and once from the perspective of the corresponding partner j who reports the mirror exports (mirror imports). In theory, these mirrored values should be equal to one another, plus or minus unobserved latent factors, and statistical noise. Moreover, the quality of countries' declarations to UN Comtrade will vary according to country, commodity, and year-specific idiosyncracies. The true unknown value of the trade is assumed to lie somewhere in between: it is a convex combination of declarations made by i and j. The "atlas" method adopts both a *residual* and a *reconciliation* approach to estimating misinvoiced trade. First, reported imports are "cleaned" from predictors of trade discrepancies and converted to a FOB basis. Second, the harmonization procedure suggested by Gaulier and Zignago (2010) is applied to produce a "reconciled value" of the trade, which is a weighted average of reporter and partner declarations according to the quality of the declaration of each country. The weights corresponding to declaration quality are calculated according to a regression of trade gaps on reporter, partner, commodity, and year fixed effects to isolate the relative quality of declarations by i and j (Gaulier and Zignago, 2010). The procedure is applied twice to generate a reconciled value for imports and one for exports. Finally, misinvoiced imports are calculated as the difference between the reconciled import value (which has been stripped of the licit predictors of trade gaps, hence the "residual" approach) and reported imports; while misinvoiced exports are equal to the difference between the reconciled export value and reported exports.

The methodology offers some refinements that are designed to ameliorate long-standing problems in the estimation of trade misinvoicing that have been highlighted in the literature. These innovations are designed to improve the validity of trade misinvoicing estimates according to the criteria established in section 3.1.

Criterion 1. *Avoid uncritically equating observed trade irregularities with misinvoicing.*

The methodology does not directly use (adjusted) trade gaps as proxies for misinvoicing. With the exception of Gara et al. (2019) who use the residuals of an econometric regression of trade gaps on legal determinants as the proxy, the other studies presented earlier that use either the DOTS-based or the UN Comtrade method have in common that trade misinvoicing is taken to be some measure of trade gaps between reported and mirror trade values, that may or may not have been adjusted for transport costs and/or re-exporting distortions. However, the existing econometric models that have been used to estimate the CIF margin do not factor in the possibility of misinvoicing, and so run the risk that the adjustment factor used to net import values from the cost of insurance and freight is actually picking up misreporting rather than transaction costs.

By contrast, the methodology presented here takes additional precautions to avoid uncritically equating trade irregularities with illicit activity. Misinvoiced trade is calculated indirectly using a "residual" approach that takes the difference between a harmonized value that represents the best quality estimate of the transaction, and import values that have been cleaned of the licit predictors of discrepancies. Since import values are systematically cleaned from most licit predictors, the remaining discrepancies must be due to illicit factors and statistical noise. Moreover, this value is not directly compared to the mirror trade value, but rather to a harmonized value that takes into account the quality of declarations. Details on this calculation are provided in section 4.3.5. Therefore, the strategy to avoid indiscriminately deducing IFFs from observed trade irregularities rests on both a residual and a reconciliation/harmonization (which are used interchangeably here) strategy.

Note that this "residual" approach (indirectly) assumes that remaining trade discrepancies that *cannot* be accounted for due to benign reasons are the result of *either* deliberate misinvoicing or statistical noise. In an alternative approach, one could assume that only the portion of trade discrepancies that *are* explained by predictors of illicitness are related to trade misinvoicing. However, this approach would suffer from a major limitation: predictors of illicit activity for which there is good data cover only a small share of the motivations for trade misinvoicing, and estimating trade misinvoicing as the share of trade discrepancies attributable to these factors would likely miss the majority of trade misinvoicing. For this reason, the indirect approach of the "atlas" method is preferred.

Criterion 2. ***Partition the trade transaction into licit and illicit components in order to account for persistent non-illicit reasons for discrepancies.***

The "atlas" methodology remedies one of the main criticisms levelled against extant misinvoicing measures – that trade gaps could in fact be due to persistent non-illicit reasons rather than foul play – by explicitly partitioning the trade transaction into its respective licit and illicit components (plus statistical noise). In related work, Fisman and Wei (2009) and Kellenberg and Levinson (2019) use econometric models to estimate the share of trade discrepancies due to predictors of the level of illicit activity in an economy, e.g., corruption. Though they do not do so, Fisman and Wei (2009) point out that one could estimate trade misinvoicing based on such a model, that is, by assuming that the portion of trade discrepancies that is not explained by predictors of licit discrepancies (e.g., distance between countries, reporting mistakes, etc.) is due to trade misinvoicing. This is the "residual" approach that this paper adopts (though the "atlas" model uses different predictors and also conducts an additional "harmonization" step). By explicitly including predictors of both licit and illicit discrepancies in the regression, the "atlas" measure seeks to estimate more accurately both a) what portion of trade discrepancies is actually explained by trade costs and other benign factors and b) what portion is illicit.

Moreover, the method supplements the traditional predictors of CIF costs (such as distance or barriers to trade) with a new approach to econometrically adjust for asymmetric reporting of re-exports and delays in the arrival of shipments. Full details on how the estimated trade gaps are partitioned are given in section 4.3.2.

Criterion 3. ***Account for the variance in countries' statistical reporting.***

The third main innovation of the "atlas" measure is that it does not take country declarations as given. The first generation of estimates implictly assumed that reporting from developed countries could be better trusted than declarations from poorer countries (see, e.g., Ndikumana and Boyce (2010)). While it may be the case that economic development correlates with the robustness of a country's statistical reporting procedures (Jerven, 2013), this is not necessarily always the case, and hence this imposed a strong assumption on the problem. Likewise, making *no* adjustment between the reporter declarations and the partner declarations makes the implicit assumption that the declarations on either end of the transaction are equally precise, which is not likely to hold in practice.

The approach presented here addresses this problem by empirically determining the relative quality of reporter and partner declarations. In addition, the quality of reporting may differ not only due to country idiosyncracies, but also due to the particularities of the reporting regime for a certain commodity (see the example of gold described under criterion 1) and year-specific shocks. Therefore, the "atlas" measure presented in this paper follows a reconciliation procedure proposed by Gaulier and Zignago (2010) to improve the quality of bilateral trade statistics. A reconciled valued of the trade is calculated using weights that minimize variance and adjust for country, commodity, and time-specific idiosyncracies. Reporting distances are estimated using an econometric model that contains reporter, partner, commodity, and year fixed effects. This has the effect of estimating the quality of a given country's customs declaration independent of its product specialization (Gaulier and Zignago, 2010). Finally, the harmonization procedure computes a variance-minimizing weighted average of country declarations to ascertain with greater precision the value of the trade on an FOB basis. See 4.3.4 for further details of this procedure.

The methodological refinements offered above strive to increase the theoretical cogency of the measure. Next, the features of the "atlas" measure described below pertain to its practical usability by academics and practitioners.

Criterion 4. ***Scale across countries and over time.***

There is broad academic and policy interest in obtaining a measure of trade misinvoicing that has a wide coverage (Cobham and Janský, 2020; UNECA, 2018a) to obtain a global picture of the extent of illicit finance. The "atlas of misinvoicing" provides comprehensive bilateral estimates of misinvoicing for 167 jurisdictions over 2000-2018.

This is possible thanks to the nature of the data source that is used (UN Comtrade) and to the relatively undemanding data requirements of the methodology. As mentioned earlier, some studies use reported quantities of the traded goods to adjust for the quality of country declarations. While this method has its merits, it may ignore misinvoicing where reported quantities or weights are different, e.g., where shipments are smuggled at either export or import but not both or where weights are mis-stated (Forstater, 2018). Moreover, the method is not applicable for countries that do not report weight or quantity data, which is the case for most African countries. The "atlas" measure only relies on observations of the price of the traded good, which has much better coverage than data on quantities, which permits the scaling of this measure across many countries and over time. The nature of the data and a more detailed description of the methodological choices regarding the data are described in section 4.1.

Criterion 5. ***Provide enough granularity to support policy prioritization.***

The "atlas" method generates estimates that are disaggregated by commodity sector at a level of resolution that allows sectoral analysis, but that is not so disaggregated that the results are less robust (for more details, see section 4.1).

In order to support evidence-based policy-making in the fight against illicit financial flows, the estimates are disaggregated by trading partner and by commodity. The initiatives needed to combat illicit flows will sometimes necessitate a sectoral approach or regional cooperation, and the disaggregated estimates will be useful to indicate where those initiatives might bear fruit.

The "atlas" database also offers summary datasets that present aggregate results and are designed to facilitate further analysis by researchers and to support targeted policy interventions. These datasets demonstrate the different lenses that can be applied to the "atlas" measure (e.g., by country, sector, etc.); they variously provide gross outflows, gross inflows, and net flows by income group, geographical region, development status, and commodity sectors.

Criterion 6. ***Use open government data.***

Finally, the "atlas" method makes use of the UN Comtrade database which, as mentioned above, broadly meets the criteria of open government data. Moreover, the method does not require any additional data, such as a separate database of transport costs (see, e.g., Schuster and Davis (2020)). The less onerous data requirements of this method further facilitate its accessibility and reproducibility by interested researchers and other stakeholders. The results of the "atlas" method are available online in a publicly available database.[26]

While this section has highlighted the salient features of the "atlas of misinvoicing" measure that seek to offer various refinements, the following section provides a full account of the methodology and detailed steps to replicate the measure. Finally, the "atlas" has surfaced key insights about the global, regional, and sectoral patterns of illicit trade; those findings are presented in section 5.

4 Methodology

4.1 Data

The data used by the "atlas" measure come from the United Nations Commodities Trade Database (Comtrade), which provides disaggregated commodities trade data using the Harmonized System (HS), the international nomenclature for trade classification, which assigns commodities to a certain product category that can be hierarchically mapped to a less

[26] Available at `https://doi.org/10.5281/zenodo.3610557`.

detailed product category, and so on. The entire Comtrade database was scraped for all participating jurisdictions and all commodities over a panel of 20 years. At the lowest level of commodity aggregation, the raw data contains approximately 490 million observations. The "atlas" measure uses data at the 2-digit level of aggregation, which is made up of 99 "chapters" (groupings of commodities). The raw data panel contains trade flows from 1999 to 2019 for 236 distinct jurisdictions. Prior to implementing data cleaning procedures, the sample size at the 2-digit level of aggregation is 23,266,944. One unit of observation consists of a reporter-partner-commodity-year quadruple, where the commodity belongs to one of the 99 HS chapters.

The 2-digit level is chosen to avoid the risk that accidental misreporting of the customs code by customs officers, or differences in national nomenclature (see Van Rensburg (2016)), result in "false positive" identification of trade misinvoicing. A plausible assumption is that, while the 6-digit or 4-digit code may be incorrectly reported due to the number of detailed product categories that could be assigned to a shipment, this is less likely with the 2-digit code since it represents a higher level of aggregation. This means that the estimates are conservative, since they will leave out instances where the customs code is deliberately falsified to benefit from lower taxes or subsidies, but where the false customs code still falls within the same 2-digit chapter as the correct code (see Kravchenko (2018)). Moreover, this will also result in "within-sector netting", i.e., inflows and outflows between the same country pair for the same 2-digit commodity code will be netted against one another. Therefore, researchers can interpret estimates as a lower bound.

4.2 Notation and conceptual model

It is instructive to define the notation that will be used throughout the rest of the paper. Let i index reporters, j index partners, c denote the commodity, and t denote the year. The value of the trade is denoted by V, and superscripts denote whether the trade flow corresponds to an import V^M or an export V^X. For ease of exposition, it is usually possible to remove the commodity and year subscripts without loss of generality.

Exports are considered net of re-exports, that is, $V_{ij}^X = V_{ij}^{exports} - V_{ij}^{re-exports}$. Unless otherwise stated, when the paper refers to exports, it designates net exports.

The declarations in Comtrade are thus:

V_{ij}^{M} Imports reported by country i from country j

V_{ij}^{X} Net exports reported by country i to country j

V_{ji}^{X} Net exports reported by i's partner, which is the mirror value of V_{ij}^{M}

V_{ji}^{M} Imports reported by i's partner, which is the mirror value of V_{ij}^{X}

As explained in section 2, the estimand of interest is the amount of trade misinvoicing both in the imports and the exports of the *reporters*. In turn, estimating the misinvoicing for reporters will yield the misinvoicing for partners. Therefore, "import values" and "export values" will refer to the import and export declarations, respectively, made by i. References to "mirror values" denote the corresponding trade flow recorded by the partner j. Since illicit flows are estimated from the perspective of the reporter, an illicit outflow will be considered to flow out of reporter i to partner j, and an illicit inflow will be considered to flow into reporter i from partner j.

The "atlas" method models the import transaction that is declared by reporter i as:

$$V_{ijct}^{M} = V_{jict}^{X} + licit + illicit + u_{ijct} \tag{1}$$

According to the model, imports reported by country i from partner j are equal to what the partner declared that it exported to country i, some amount of licit discrepancies (which can be positive or negative) due to benign or non-illicit reasons, trade misinvoicing (which can be positive or negative), and statistical noise.

Likewise, the export transaction occurring at i's customs is conceptualized as:

$$V_{jict}^{M} = V_{ijct}^{X} + licit + illicit + v_{ijct} \tag{2}$$

These two models underpin the "atlas" method of estimating the illicit financial flows that occur at a given country i's customs in both imports and exports, respectively.

4.3 Step-by-step procedure to calculate misinvoicing in imports and exports

The illicit flow in each transaction is estimated following a strategy that proceeds in three broad steps:

1. Estimate the discrepancies between mirror trades as a function of both licit and illicit

predictors.

2. Perform a harmonization procedure in order to generate a reconciled value that represents the best estimate of the FOB value of the trade taking into account the relative quality of the declaration by the countries.

3. Calculate the IFF embedded in each transaction as the difference between the observed value (adjusted to remove the contribution of licit predictors) and the reconciled value.

The specific steps are detailed below.

4.3.1 Data cleaning

First, data cleaning procedures are implemented to remove unmatched or orphaned transactions (i.e., transactions that do not have a corresponding mirror value), and to remove observations that do not correspond to countries.[27] The sample size decreases from $n =$ 23,266,944 to $n =$ 2,559,456. The large drop partly reflects the fact that there exist many orphaned transactions where, for any given country, commodity, and year, the import declaration V^M_{ijct} is in the data but the corresponding mirror export value V^X_{jict} does not exist, or where the export declaration V^X_{ijct} is observed but the mirror import value V^M_{jict} is not. Missing mirror values in the data could either be due to illicit activity or could be explained by other factors such as shaky statistical reporting practices of certain customs authorities (Jerven, 2009) – though it is not easy to disentangle those reasons. Since the estimation strategy of the "atlas" measure relies on bilateral trade asymmetries to calculate misinvoicing (though with adjustments, as discussed), it will not capture all types of illicit activity that can occur with merchandise trade – but this is a feature, not a bug, of trade misinvoicing measures where the estimand of interest is "technical smuggling", as opposed to "pure smuggling" where goods (e.g., illicit drugs) are exported clandestinely from a country and imported clandestinely into another and which as result will not be reflected in trade gaps (Schuster and Davis, 2020).

A further 15,264 observations are removed where the observed trade gap is greater than 100, to throw out cases that might be due to genuine and egregious statistical mistakes in reporting (e.g., reporting values in dollars versus thousands of dollars). Various thresholds were experimented with and the results remain robust. Following this, a statistical cleaning procedure is performed which removes observations that have a Cook's Distance greater than 2 (no cases), and iteratively drops statistically significant outliers with Bonferonni correction

[27] Comtrade also provides declarations where the partner is not an individual jurisdiction, but an aggregate, e.g., "World", "Other Europe, not reported elsewhere", etc.

(not exhaustive).

After the data cleaning procedures are completed, the resulting panel covers 167 distinct reporting and partner jurisdictions, and has a sample size of $n = 2{,}446{,}679$.

4.3.2 Fitting gravity models

For any given country in the sample, the goal is to estimate all the trade misinvoicing that occurs at its customs, both when a country reports imports and when it reports exports to Comtrade. Therefore, two gravity models are econometrically fitted that represent the gap between the trade flow (import or export) reported by country i and the mirror trade flow reported by partner j (mirror export or mirror import, respectively) as explained by legitimate factors (e.g., reporting mistakes), discrepancies due to trade misinvoicing, and statistical noise. Since the "atlas" method operates from the perspective of the reporting country i, there are two models of the gaps between, on the one hand, reported imports and mirror exports, and on the other, reported exports and mirror imports.

As discussed previously, the methodology proceeds in this way in order to estimate illicit trade for the entire set of countries that report to Comtrade, and where the reporter i is the proverbial "atlas" from whose perspective illicit trade is systematically estimated, for both imports and exports.

Therefore, two gravity models of the form below are fitted:

$$\ln\left(\frac{V_{ijct}^{M}}{V_{jict}^{X}}\right) = \alpha_0 + \boldsymbol{X}\boldsymbol{\alpha} + \boldsymbol{Z}\boldsymbol{\gamma} + \epsilon_{ijct} \tag{3}$$

and

$$\ln\left(\frac{V_{jict}^{M}}{V_{ijct}^{X}}\right) = \beta_0 + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{Z}\boldsymbol{\lambda} + \xi_{ijct} \tag{4}$$

where the dependent variable is the gap between the transaction reported by i and the mirror transaction declared by partner j, $\boldsymbol{X}$ is a vector of licit explanations for discrepancies, and $\boldsymbol{Z}$ is a vector of illicit determinants of discrepancies. In both cases, the import values are the numerator of the trade gap, because the trade literature conventionally estimates trade gaps as a CIF-FOB margin between imports and exports (Yotov et al., 2016). Note that the import value in the numerator of the outcome variable in equation (4) corresponds to the *mirror* import value that partner j declares to Comtrade of its imports from i, while the export value in the denominator is the declaration from reporter i.

The objective is to partition the trade transaction into its respective licit and illicit components, as exhorted by criterion 2 of a credible misinvoicing measure. A transaction reported by i should be equal to the mirror value declared by i's partner j, plus factors explaining observed discrepancies, plus statistical noise. Import declarations include CIF and so will need to be converted to a FOB basis to be comparable to exports; this is accomplished by dividing the import declaration with the estimated coefficients on the factors that can explain observed discrepancies, thus "stripping" import values of the margin (which in existing methods is assumed to reflect transaction costs only) that is econometrically estimated. Moving the mirror declarations (i.e., what the partner j declares to Comtrade) to the left-hand side in equations (1) and (2) and taking logs will yield the gravity models noted in equations (3) and (4), respectively. Therefore, two models are fitted where the dependent variable is the gap between i's imports and the mirror net exports, and where the dependent variable is the gap between i's net exports and the mirror imports, respectively.

The innovation of the "atlas" methodology is that it explicitly partitions the factors that can explain trade discrepancies into those that can be attributed to benign reasons (captured in $\boldsymbol{X}$), and those that can be ascribed to underlying illicit activity (captured in $\boldsymbol{Z}$).

Thus, the vector $\boldsymbol{X}$ contains the predictors associated with non-illicit reasons of observed gaps between between mirror trade values. First, it includes traditional "gravity" variables representing various geographical factors that can be responsible for transportation and other transaction costs (Anderson, 1979; McCallum, 1995) from CEPII's *Gravity* database (Conte et al., 2021):

- $\texttt{dist}_{ij}$ and $\texttt{dist}^2_{ij}$, which are the distance between a country pair and the squared distance between a country pair, respectively;
- $\texttt{contiguous}_{ij}$, a dummy variable indicating whether the countries share a border;
- $\texttt{landlocked}_i$ and $\texttt{landlocked}_j$, which are a dummy variable indicating whether the reporter is landlocked, and a dummy variable indicating whether the partner is landlocked, respectively.

Moreover, year fixed effects are added to the models in order to control for period-specific idiosyncrasies in reporting, because a period-specific shock that affects each country's trade equally (e.g., a trade shock like a global pandemic) might partly explain the observed trade gap, for entirely non-nefarious reasons. Therefore, the vector $\boldsymbol{X}$ includes a series of year-specific indicator variables τ_t for the years $t = 2001, \ldots, 2018$ that are equal to 1 if τ_t corresponds to the year of the transaction, and 0 otherwise (omitting the first year since the models include an intercept). Implicitly, including the estimated year-specific intercepts in the vector of parameters on $\boldsymbol{X}$ and not in the vector of parameters on $\boldsymbol{Z}$ assumes that any factor leading to discrepancies that varies over time but is constant across countries is not due to illicit factors. This assumption is relatively plausible as it is difficult to think that there would be a sudden increase or decrease of criminal activity across countries globally, for instance.

The models also econometrically adjust for the other legitimate reasons that might readily explain discrepancies in bilateral trade statistics, such as when shipments arrive at their destination in a different calendar year from when they departed the country of origin, or when the asymmetric reporting of re-exports to third countries creates the illusion of discrepancies between dyads (as illustrated by the "false positive" example of Zambian copper). Thus, the "atlas" method avoids uncritically equating observed trade irregularities with misinvoicing that could be due to artifices of the recording process; and meets criterion 1 of a rigorous measure of misinvoicing.

Moreover, it is expected that the dependent variable is autocorrelated and that present values of trade gaps will depend on past values of trade gaps; and the models therefore include a lag of the dependent variable. Again, all of the factors described so far are assumed to represent persistent non-illicit reasons for discrepancies, and so they are included in the vector $\boldsymbol{X}$.

The operationalization of these explanatory variables will differ according to whether the reported transaction by i is imports or (net) exports:

- $V^M_{ijc,t+1}/V^M_{ijct}$ to capture the misreporting of imports at $t+1$ in model (3), and $V^M_{jic,t+1}/V^M_{jict}$ in model (4);
- $V^{re-exports}_{jict}/V^M_{ijct}$ to capture the misreporting of re-exports in model (3), and $V^{re-exports}_{ijct}/V^M_{jict}$ in model (4);
- $\ln\left(V^M_{ijc,t-1}/V^X_{jic,t-1}\right)$ to capture the persistence across periods in model (3), and $\ln\left(V^M_{jic,t-1}/V^X_{ijc,t-1}\right)$ in model (4).

Next, the models include, $\boldsymbol{Z}$, a vector of illicit determinants of discrepancies, composed of:

- $\texttt{corruption}_{it}$ and $\texttt{corruption}_{jt}$ of the reporter and partner, respectively, in any given year in the sample;
- $\texttt{PoorRegulation}_{it}$ and $\texttt{PoorRegulation}_{jt}$ to capture poor regulatory quality in the

reporter and the partner country, respectively, in any given year in the sample;

- $\texttt{tariff}_{ijct}$ which is the average tariff imposed by reporter i on imports of commodity c from partner j in year t in equation (3); and $\texttt{tariff}_{jict}$ which is the average tariff imposed by j on imports from i, i.e., the tariff imposed on mirror imports used in equation (4).

The variables `corruption` and `PoorRegulation` are obtained from the *Worldwide Governance Indicators* (WGI) database, and capture perceptions of the extent to which public power is exercized for private gain, and perceptions of the government's ability to formulate and implement sound policies that permit private sector development, respectively (Kaufmann et al., 2010). The inverse of the variables from the WGI database is taken so that the high end of the variables (measured by percentile rank) corresponds to high amounts of corruption and poor regulatory quality.

The tariff measure is from the UNCTAD TRAINS database (UNCTAD, 2018) and captures the incentives to misinvoice imports in order to evade tariffs.

Therefore, the estimates of the coefficients on known licit reasons for discrepancies will be contained in the parameter vectors $\hat{\boldsymbol{\alpha}}$ and $\hat{\boldsymbol{\beta}}$, depending on whether the import or the export transaction, respectively, is modeled. Likewise, coefficient estimates for illicit factors will be contained in the parameter vectors $\hat{\boldsymbol{\gamma}}$ and $\hat{\boldsymbol{\lambda}}$, respectively. These coefficients estimate the portion of the trade gap that is explained by licit (illicit) factors conditional on the illicit (licit) factors. In other words, they represent how the CIF-FOB margin varies as a result of changes in one group of factors (licit or illicit), while holding the other group of factors constant. Hence, any estimates of legitimate transport and other trade costs will be stripped of the effect of any illicit factors.

To improve the normality of the data, highly skewed predictor variables are transformed prior to fitting the gravity models. The lagged dependent variable and the variable capturing the misreporting in different calendar years are logged. The inverse hyperbolic sine transformation is applied to the variable capturing the misreporting of re-exports, since it cannot be logged due to the presence of zeroes.[28]

The vectors of parameters associated with licit and illicit factors (plus a constant) are estimated by fitting the gravity models in (3) and (4) using Ordinary Least Squares (OLS) on pooled data for the period 2000-2018. The advantage of using linear regression rather than a more flexible non-parametric model such as a Generalized Additive Model (GAM) is that

[28]The inverse hyperbolic sine function is defined as $ihs(x) = \ln(x + \sqrt{x^2 + 1})$. It can be used to reduce the skew in data where the natural log cannot otherwise be taken (since $\ln(0)$ is undefined).

it provides estimates of licit predictors that hold illicit predictors constant and vice versa. This is useful to calculate import values that are “cleaned” from benign predictors which allows interpreting the remaining discrepancies as the marginal effects due to illicit activity and statistical noise.

The estimated regression coefficients in the model where the reporter i’s declaration is imports are displayed in the left-hand side column of Table 2 below, and the estimated coefficients in the model where the reporter i’s declaration is exports are provided in the right-hand side column. Next, the estimated coefficients are briefly discussed.

	Dependent variable	
	ln.ratio_CIF	ln.ratio_CIF_mirror
	(1)	(2)
dist_t	-0.007***	-0.007***
dist_t.sq	0.000***	0.000***
contiguous	-0.156***	-0.154***
landlocked_i	0.124***	-0.098***
landlocked_j	-0.091***	0.123***
ln.FutImport_misp	-0.266***	
ihs.ReExport_misrep	0.028***	
ln.ratio_CIF_lag	0.452***	
tariff	-0.001***	
ln.FutImport_misrep_mirror		-0.282***
ihs.ReExport_misrep_mirror		0.010***
ln.ratio_CIF_lag_mirror		0.443***
tariff_mirror		-0.001***
corruption_i	-0.002***	0.001***
corruption_j	0.001***	-0.002***
PoorRegulation_i	0.000**	-0.000**
PoorRegulation_j	-0.000	0.000**
Constant	0.133***	0.138***
Year fixed effects	Yes	Yes
Observations	2,446,679	2,446,679
Adjusted R^2	0.336	0.320
Residual Std. Error (df = 2446647)	1.136	1.180
F Statistic (df = 31; 2446647)	39,925.120***	37,126.330***

Notes: *p<0.1; **p<0.05; ***p<0.01

The dependent variable ln.ratio_CIF corresponds to $\ln\left(V^M_{ijct}/V^X_{jict}\right)$.

The dependent variable ln.ratio_CIF_mirror corresponds to $\ln\left(V^M_{jict}/V^X_{ijct}\right)$.

Table 2: Regression results.

The coefficient on the distance between transacting partners (`dist`) is negative and statistically significant in both models, which runs counter to the intuition that shorter distances should be associated with smaller transport costs. Yet, the inverse relationship between distance and the trade gap is a persistent empirical result in international economics, and has been dubbed the "distance puzzle" (see, e.g., McCallum (1995); Anderson and Van Wincoop (2003); Disdier and Head (2008); Yotov (2012)). Moreover, a non-linear relationship between distance and the discrepancy in mirror statistics is expected to the extent that, for greater distances, the price discrepancy is likely to be even larger (Gaulier and Zignago, 2010; McCallum, 1995; Yotov et al., 2016). This hypothesis is supported by the fact that the coefficient on the squared distance term (`dist.sq`) is positive and statistically significant.

The coefficient on the dummy variable indicating whether the trading countries are geographically contiguous (`contiguous`) is negative and statistically significant in both models, which is to be expected.

While the coefficient in model (1) on the dummy indicating whether the reporting country (i.e., the importer) is landlocked is positive, the corresponding coefficient for the partner country (i.e., the exporter) is signed contrary to expectation. If part of the price discrepancy is due to access and transport costs, the price discrepancy would be expected to rise if a country is landlocked, everything else constant. Nevertheless, Gaulier and Zignago (2010) also find a negative sign on the coefficient on landlocked exporters. Model (2) reports similar findings, where the coefficient is negative for landlocked exporters and positive for landlocked importers (the reporter and partner, respectively, in this model).

The coefficient on the misreporting of imports in the next calendar year is negative and statistically significant for both models. That is, when the ratio between a given country's imports at time $t+1$ and at time t increases (for the same partner and commodity), indicating that shipment arrivals were higher in the next calendar year, then the price discrepancy between imports at time t and corresponding mirror exports tends to decrease (holding other factors constant). This suggests that part of the observed discrepancy in bilateral trade statistics is simply due to calendar differences in the recording of shipments.

Both models also control for the misreporting of re-exports by including the share of re-exports in the other country's imports as an independent variable. Re-exports are the exports of foreign goods in the same state as previously imported and are recorded by the re-exporting country as exports.[29] However, the country of final destination (i.e., the importer) will tend to see the goods as coming from the country where value was last added, that is, earlier on in the value chain. This introduces artificial discrepancies in bilateral

[29] See Comtrade database description: `https://unstats.un.org/unsd/tradekb/Knowledgebase/Reexports-and-Reimports`.

trade statistics. To counter this, the dependent variable uses exports net of re-exports, which thus represents exports of domestic goods only. Moreover, the share of a partner's re-exports in the corresponding reporter's imports for a particular commodity-year is included as an explanatory variable. Results for both models show that an increase in that ratio is associated with an increase in the observed discrepancy in mirror trade statistics, *ceteris paribus*; which supports the hypothesis that part of the gaps in mirror trade statistics can be explained by the misreporting of re-exports.

Finally, as expected, the positive and statistically significant coefficient on the lagged value of the dependent variable in both models suggests that observed discrepancies are persistent over time.

All the coefficients discussed so far can be treated as non-illicit predictors of observed discrepancies in bilateral data. They capture either legitimate factors that would increase the price of imports, such as the cost of freight, or reflect artifices that occur during the recording of the data. Next, the coefficients that capture drivers of the discrepancies that may have an illicit motivation or nature, such as escaping barriers to trade or poor governance, are discussed.

One of the more surprising results in the models is that import tariffs are associated with a decrease in the observed price discrepancy (everything else held constant): the coefficient on the average tariff line imposed by a country on a specific commodity-year-exporter is negative and statistically significant (in both models). This finding is robust to different model specifications. One possible explanation is as follows. Customs officials are trained to protect revenues rather than to look for misinvoicing that may occur for other reasons (Mikuriya, 2018). As such, they are likely to concentrate their audit efforts on shipments with high *ad valorem* tariffs attached. If misinvoicers are aware of this, they are more likely to direct the bulk of their faking efforts on items at lower tariff lines to evade detection. This phenomenon would explain the negative sign on the `tariff` coefficient. Jean et al. (2018); Kellenberg and Levinson (2019) also find that higher tariffs may result in lower customs duty evasion. In addition, Patnaik et al. (2008) also find that higher tariffs result in lower over-invoicing of imports, which is a key source of illicit financial outflows. They note that higher tariffs would reduce the incentive to over-invoice for imports as doing so would result in firms having to pay higher tariffs.

To capture poor governance in the transacting countries, the models include variables measuring corruption and poor regulatory quality with respect to private sector development. Most of these coefficients are signed according to expectation. However, the coefficients on corruption in importers are negative and statistically significant (`corruption_i` in the first model and `corruption_j` in the second model correspond to the importer). Likewise, the coefficients on poor regulation in exporting countries are negative. This may be because poor governance reduces trade misinvoicing to the extent that it makes other channels of illicit financial flows (e.g., use of the formal financial system, cash smuggling, etc.) easier to use (Ferwerda et al., 2013), or to the extent that those involved in illicit finance have less of a need to hide their illicitly-obtained funds abroad, reducing the extent of illicit outflows for a given level of proceeds of corruption (Walker, 1999).

Finally, potential issues of multicollinearity are examined by looking at the Variance Inflation Factor (VIF) scores for the coefficients in each model, reported in Table 3 below. The high VIF for the coefficients on distance and distance squared are not a cause for concern and are to be expected given that the models include a quadratic term and its lower-order term. Multicollinearity does not bias OLS coefficients, but it does inflate standard errors, making it harder to detect statistically significant relationships. The high VIF values for the variables capturing corruption and poor regulation occurs because they are highly correlated with each other – indeed, a highly corrupt country is likely to have a poorly governed regulatory system. The high VIF value for poor regulatory quality in the partner country ($\texttt{PoorRegulation}_j$) might explain why this coefficient is not statistically significant in model (1). Despite this, the variable is still included in the model since poor governance, as a driver of misinvoicing, is likely to operate on both sides of the transaction. Moreover, the estimates of interest here are the implied CIF rates due to legitimate and illegitimate predictors, which are found by accounting for the marginal effect of coefficients, which will still be unbiased despite the multicollinearity. Thus, it is important to retain theoretically important predictors in the model.

	Model	
	(1)	(2)
dist	15.22	15.22
dist.sq	15.319	15.319
contiguous	1.091	1.09
landlocked_i	1.026	1.026
landlocked_j	1.026	1.026
ln.FutImport_misrep	1.011	
ln.FutImport_misrep_mirror		1.011
ihs.ReExport_misrep	1.011	
ihs.ReExport_misrep_mirror		1.011
ln.ratio_CIF_lag	1.015	
ln.ratio_CIF_lag_mirror		1.015
tariff	1.046	
tariff_mirror		1.046
corruption_i	6.864	6.865
corruption_j	6.869	6.867
PoorRegulation_i	6.955	6.902
PoorRegulation_j	6.905	6.958
factor(year)	1.046	1.046

Table 3: Variance Inflation Factors of the models.

4.3.3 FOBization of imports

After estimating the gravity models, the third step is to "FOBize" imports by deflating them from transport and other costs, so that they are on the same basis as export declarations, in order to be able to compare them.

Subscripts for commodities c and years t are henceforth omitted for simplicity.

FOBized imports for reporter i are given by:

$$V_{ij}^{M;FOB} = \frac{V_{ij}^{M}}{\exp(\hat{\alpha}_0 + \boldsymbol{X}\hat{\boldsymbol{\alpha}} + \boldsymbol{Z}\hat{\boldsymbol{\gamma}})} = V_{ji}^{X} \cdot \exp(\hat{\epsilon}_{ij}) \tag{5}$$

The reported import value is stripped of the implied CIF margin given by the estimated coefficients in the gravity model represented in equation (3). Note that this formulation implies that FOBized imports are equal to mirror exports plus statistical noise.

As a robustness check, the residual $\hat{\epsilon}_{ij}$ was also stripped from import values, to investigate the consequences of a differing assumption which would hold that the CIF margin includes statistical noise. The findings remain similar.

Equivalently, FOBized imports for partner j are calculated as:

$$V_{ji}^{M;FOB} = \frac{V_{ji}^{M}}{\exp(\hat{\beta}_0 + \boldsymbol{X}\hat{\boldsymbol{\beta}} + \boldsymbol{Z}\hat{\boldsymbol{\lambda}})} = V_{ij}^{X} \cdot \exp(\hat{\xi}_{ij}) \tag{6}$$

where mirror imports are stripped of the coefficients estimated in equation (4).

The estimated CIF margin between reporter imports and mirror exports is 1.73 and the estimated CIF margin between reporter exports and mirror imports is 1.72. Conceptually, the true (unobserved) CIF margin should be 1 plus CIF plus statistical noise. The results show that the estimated margins are much larger than is commonly assumed in the literature (see Gaulier and Zignago (2010)), and suggests that the commonly assumed CIF margin of 1.1 used in some trade misinvoicing estimates is inadequate (see, e.g., UNCTAD (2016); Spanjers and Salomon (2017)).

Further, imports are not FOBized for the countries that do not report their imports to Comtrade on the recommended CIF basis. For these countries, the FOBization procedure is not performed, and instead the reported import values are simply used.[30]

In a separate step, FOB imports are also calculated by stripping out the estimated *licit* components of the CIF margin. Recalling that in the models defined by equations (1) and (2), the true (unobserved) bilateral trade considers reporter imports as equivalent to partner exports, plus discrepancies and statistical noise. Thus, the trade discrepancies are partitioned into those originating from licit sources (e.g., reporting mistakes) and those that can be explained by illicit motivations and thus are likely to represent trade misinvoicing, e.g.: $V_{ijct}^{M} = V_{jict}^{X} + licit + illicit + u_{ijct}$. Licit predictors are included in vector $\boldsymbol{X}$ while illicit predictors are contained in $\boldsymbol{Z}$.

Reporter imports that are stripped out of the licit components of the CIF margin are called $V_{ij}^{M;FOB,nonIFF}$, where the superscript refers to the component of the trade gap that has been

[30]Those countries are Brazil, Cambodia, Canada, Guinea, Mali, Paraguay, South Africa, Tajikistan, Ukraine, and the USA. For more information, see https://unstats.un.org/unsd/tradereport/questform_MM.asp?qid=7.02.

stripped out. Likewise, partner FOB imports cleaned from the legitimate components of the CIF rate are denoted $V_{ji}^{M;FOB,nonIFF}$.

In this calculation, import values are divided by the estimated coefficients of the variables in the vector $\boldsymbol{X}$ that contains legitimate sources of discrepancies, such as misreporting due to different calendar years or due to re-exports. This implies that the other side of the trade is exports plus illicit discrepancies plus statistical noise.

$$V_{ij}^{M;FOB,nonIFF} = \frac{V_{ij}^{M}}{\exp(\hat{\alpha}_0 + \boldsymbol{X}\hat{\boldsymbol{\alpha}})} = V_{ji}^{X} \cdot \exp(\boldsymbol{Z}\hat{\boldsymbol{\gamma}}) \cdot \exp(\hat{\epsilon}_{ij}) \tag{7}$$

$$V_{ji}^{M;FOB,nonIFF} = \frac{V_{ji}^{M}}{\exp(\hat{\beta}_0 + \boldsymbol{X}\hat{\boldsymbol{\beta}})} = V_{ij}^{X} \cdot \exp(\boldsymbol{Z}\hat{\boldsymbol{\lambda}}) \cdot \exp(\hat{\xi}_{ij}) \tag{8}$$

The illegitimate components of the CIF margin are estimated to be $\exp(\boldsymbol{Z}\hat{\boldsymbol{\gamma}}) = 0.98$ and $\exp(\boldsymbol{Z}\hat{\boldsymbol{\lambda}}) = 0.97$. This implies that, holding legitimate reasons for trade gaps constant, the part of the trade gap that is explained by illicit factors alone would result in import over-invoicing or export under-invoicing (an illicit outflow).

4.3.4 Harmonization procedure

The following step seeks to remedy the one of the main problems identified in the literature, where most existing estimates make no attempt to account for the variance in the trade declarations of countries. Therefore, the next step is designed to fulfill criterion 3 presented above. A harmonization procedure is performed to generate the best estimate of the FOB value of the trade, following the reconciliation technique developed by Gaulier and Zignago (2010). The harmonization procedure rests on the view that different countries' declarations to customs will vary in reporting quality due to country-specific idiosyncrasies (e.g., robustness of national statistical procedures, etc.). For any given trade value, there are two declarations: one from the reporting country and one from the partner country. Thus, the goal is to generate a reconciled value as a weighted average of both declarations, where weights are proportional to a country's *relative* quality of declaration.

To implement the harmonization procedure, the two regression models below are used, where the outcome variable is the reporting distance between: in (9), reporter imports (previously FOBized using the procedure described above) and mirror exports; and in (10), reporter exports and mirror imports (on a FOB basis). The models employ reporter, partner, commodity, and time fixed effects to control for country-specific, commodity-specific, and year-specific idiosyncrasies in the trade gaps.

$$\left| \ln \frac{V_{ijct}^{M;FOB}}{V_{jict}^{X}} \right| = \phi_i + \psi_j + \kappa_c + \tau_t + \varepsilon_{ijct} \tag{9}$$

$$\left| \ln \frac{V_{jict}^{M;FOB}}{V_{ijct}^{X}} \right| = \phi_i + \psi_j + \kappa_c + \tau_t + \varepsilon_{ijct} \tag{10}$$

where

- ϕ_i are reporter fixed effects;
- ψ_j are partner fixed effects;
- κ_c are commodity fixed effects;
- τ_t are year fixed effects;
- ε_{ijct} is random noise;
- and with a sum-to-zero constraint for identifiability: $\sum_{i=1}^{I} \phi_i + \sum_{j=1}^{J} \psi_j + \sum_{c=1}^{C} \kappa_c + \sum_{t=1}^{T} \tau_t = 0$.

The fixed effects of interest are ϕ and ψ which reflect the accuracy of each transacting country's reports to Comtrade. The commodity and year fixed effects isolate the source of discrepancies that are independent of the quality of country declarations, e.g., a product code that is more prone to reporting mistakes because the merchandise is homogeneous and hard to distinguish (Gaulier and Zignago, 2010). Therefore, this means that the report and partner fixed effects are "cleaned" from the effects of any trade specialization in certain sectors (Gaulier and Zignago, 2010). Therefore, the estimated fixed effects $\hat{\phi}$ and $\hat{\psi}$ represent the marginal effect of a country's specific reporting practices on the trade gap, holding the quality of their partner's declaration constant and independent of any commodity or year-specific reasons for the gap between the mirror declarations.

Weights are computed in order to minimize the variance of the reconciled value, following the procedure originated by Gaulier and Zignago (2010).

As in Gaulier and Zignago (2010), the variance in reporter quality of declaration is computed as:

$$\sigma_i = \frac{\pi}{2} \cdot \left(\hat{\phi}_i - \min(\hat{\boldsymbol{\phi}}) - 2 \cdot SE(\hat{\phi}_i) \right) \tag{11}$$

and for the partner quality of declaration as:

$$\sigma_j = \frac{\pi}{2} \cdot \left(\hat{\psi}_j - \min(\hat{\boldsymbol{\psi}}) - 2 \cdot SE(\hat{\psi}_j) \right) \tag{12}$$

where $\hat{\phi}_i$ and $\hat{\psi}_j$ are the estimated least-square means of country-specific discrepancies for the ith reporter and the jth partner, respectively; and $SE(\hat{\phi}_i)$ and $SE(\hat{\psi}_j)$ are the corresponding standard errors of those fixed effect coefficients.

Next, the weight to give to the reporter i's declaration as opposed to the partner j's declaration is computed as:

$$\delta = \frac{e^{\sigma_j^2} \cdot \left(e^{\sigma_j^2} - 1 \right)}{e^{\sigma_i^2} \cdot \left(e^{\sigma_i^2} - 1 \right) + e^{\sigma_j^2} \cdot \left(e^{\sigma_j^2} - 1 \right)} \tag{13}$$

The next step is to compute the reconciled value, which represents the most precise estimate of the value of the trade by taking into account the quality and accuracy of each country's declaration. The reconciled value RV^M represents the best estimate of the import declaration.

$$RV^M = \delta \cdot V_{ij}^{M;FOB} + (1 - \delta) \cdot V_{ji}^X \tag{14}$$

The reconciled value RV^X represents the best estimate of the export declaration.

$$RV^X = \delta \cdot V_{ij}^X + (1 - \delta) \cdot V_{ji}^{M;FOB} \tag{15}$$

Note that in equation (14) the reporter i declares import transactions while in equation (15) it declares the value of its exports, and that the weight δ represents the relative precision of i's declaration compared to its partner j's. Therefore, instead of assuming that, e.g., declarations by developed countries are more trustworthy than declarations by poor countries, the relative accuracy of each country's declaration is determined empirically.

4.3.5 Computing the illicit flow embedded in each transaction

The final step is to compute the dollar value of trade misinvoicing contained in both imports and exports for the "atlas" reporter i.

The import discrepancy for country i is the difference between FOB imports stripped of licit trade discrepancies (so all that remains is the illicit gap plus statistical noise) as calculated in (7) and the reconciled value that represents the best estimate of reporter FOB imports controlling for the reporting quality of countries calculated in (14). This strategy represents the combination of a "residual" and "reconciliation" approach, and is one of the main innovations of the "atlas" method, as discussed in section 3.3.

Specifically, recall that $V_{ij}^{M;FOB,nonIFF}$ denotes imports that have been stripped of the estimated margin that can be explained by non-illicit factors alone, and is equal to $V_{ji}^{X} \cdot \exp(\boldsymbol{Z}\hat{\boldsymbol{\gamma}}) \cdot \exp(\hat{\epsilon}_{ij})$ as shown in equation (7). This follows from the data-generating model for a trade transaction discussed in section 4.2 – which is based on the macroeconomic identity that the true value of imports by i from j is equal to the true value of exports by j to i. Of course, the true value of the trade is unknown, and so the "atlas" method provides a model of the trade *declarations* where declarations by i are on one side of the equality, and the corresponding mirror declarations by j plus discrepancies and statistical noise are on the other side of the equality. By stripping import declarations of the discrepancies that can be explained by licit or benign factors, what remains on the other side of the equality are mirror exports, discrepancies that can be explained by determinants of illicitness, and the unexplained discrepancies (the residual). In other words, what remains on the other side of the transaction is the misinvoiced mirror export declaration (plus noise) – this is the nature of the "residual" approach.

Then, the reconciled value RV^M is the one that harmonizes declarations from both reporter and partner according to relative precision, and thus represents the best estimate of the "true" declaration (which lies somewhere between what the reporter declared and what the partner declared) – this is the nature of the "harmonization" or ("reconciliation") strategy of the "atlas".

Therefore, by subtracting the best guess of the true import declaration from the misinvoiced mirror export declaration (plus noise), what remains is the dollar amount of misinvoicing in i's imports from j.

$$IFF_{ij}^{M} = V_{ij}^{M;FOB,nonIFF} - RV^{M} \tag{16}$$

Positive values of IFF_{ij}^{M} correspond to import over-invoicing, i.e., an illicit outflow from i to j.

Using the same reasoning, the export discrepancy for country i is the difference between the reconciled value that represents the best estimate of reporter exports as calculated in (15) and the observed exports actually reported by i.

$$IFF_{ij}^X = RV^X - V_{ij}^X \tag{17}$$

Positive values of IFF_{ij}^X correspond to export under-invoicing by i and represent an illicit outflow from i to j.

Total trade misinvoicing for a reporter i trading with partner j for commodity c at time t is the sum of the import discrepancy and of the export discrepancy.

A summary of the step-by-step procedures is provided in Figure 2 below.

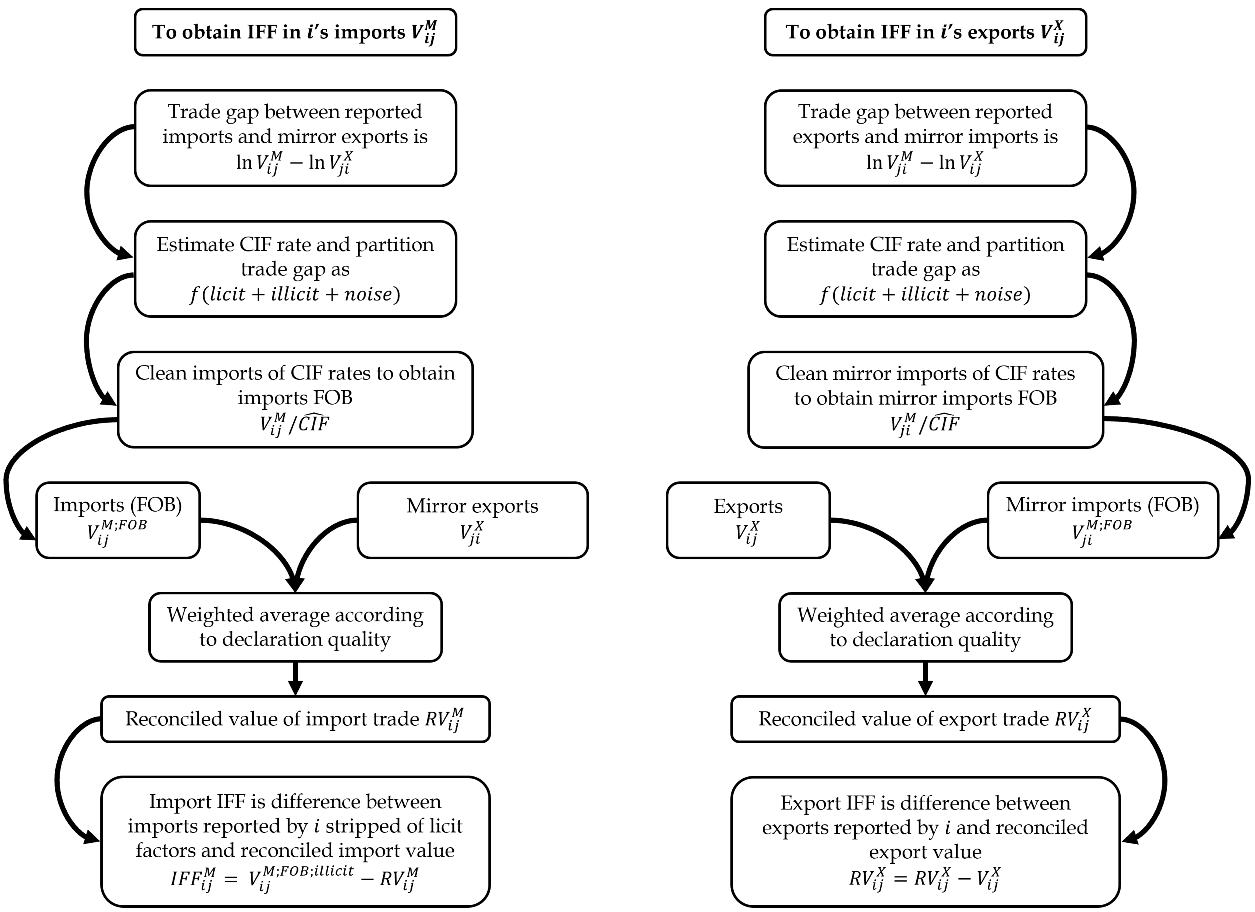

Figure 2: Main steps of the methodology to generate the "atlas of misinvoicing" estimates.

4.4 Aggregation strategy

The prior section provided the detailed steps to arrive at an estimate of the illicit flow embedded in a particular transaction between a reporter i and a partner j for a commodity

c in year t. Illicit flows are then aggregated up to have an estimate of illicit flows for a particular country i. Broadly, aggregate IFFs can be presented on a "net" or on a "gross excluding reversals" (GER) basis (Salomon, 2019). The question of what technique to use to aggregate IFFs is more difficult than it seems, and has been the subject of vigorous disagreements by authors (see, e.g., (Nitsch, 2016; Spanjers and Salomon, 2017)).

Illicit flows presented on a net basis simply add up inflows (a negative value) and outflows (a positive value). Thus, positive and negative values will cancel out to yield a smaller number of aggregate IFFs for country i.

However, as argued by GFI, there is no such thing as "net crime" (Cobham and Janský, 2020), and so it makes sense to consider gross flows. Illicit outflows presented on a GER basis ignore all inflows (i.e., negative values) and simply add up all the positive outflows across trading partners. Analogously, illicit inflows on a GER basis are calculated by summing only negative values across partners (i.e., ignoring outflows). As this paper has argued, illicit inflows are also prejudicial to development since they are untaxed and invisible to governments. Illicit inflows can exacerbate resource curse issues and can be used to finance illegal activities such as drug trafficking and terrorism. Therefore, estimates of illicit inflows from trade misinvoicing should also be a quantity of interest.

It is important to note that for a given country pair i and j in a given year t, the same trade flow can be associated with either an inflow or an outflow according to what commodity is traded. While it might seem unlikely that illicit funds might be traveling in both directions for the same trade flow, there could be a variety of different actors doing this for different reasons. For example, country i might have export taxes on raw materials and export subsidies for manufacturing output, which would give an incentive to under-invoice exports of raw materials (resulting in an illicit outflow) and to over-invoice exports of manufactured goods (resulting in an illicit inflow). Alternatively, a criminal syndicate that has a legitimate front company may use re-invoicing to send money to an affiliate in another country to make an investment (e.g., hiring "muscle" to fight off a competitor) and then bring funds back using exports to the same country when the investment bears fruit.

Therefore, an aggregation strategy that nets out the illicit inflows and outflows might risk under-estimating the extent to which illicit activity occurs within a trade flow for the same country pair. Conversely, if illicit flows are presented on a GER basis, this should not be equated to funds departing a country, since inflows would not be included in the calculation. In addition, contrary to the GFI estimates (Spanjers and Salomon, 2017; Salomon, 2019), GER inflows and GER outflows are not summed, recognizing the critique by Nitsch (2012) that such an aggregate figure is so hard to interpret that it is devoid of any substantive meaning.

The object of analytical inquiry should guide the choice of aggregation strategy. For example, stakeholders interested in getting a picture of the total amount of funds departing a country on balance should favor a net aggregation basis. By contrast, stakeholders interested in better understanding the drivers and mechanisms of IFFs should favor aggregation using GER to identify where money is flowing in or out. In that way, IFFs presented on a GER basis can aid in tailoring policy responses across jurisdictions and sectors.

The "atlas" database provides aggregated results using both aggregation strategies. Since positive values represent illicit outflows and negative values represent illicit inflows, to calculate gross outflows on a GER basis, the positive values across j are summed for each reporter i.

$$IFF_{it}^{gross;out} = \sum_{j;IFF>0} IFF_{ijt}^{M} + \sum_{j;IFF>0} IFF_{ijt}^{X} \tag{18}$$

To calculate gross inflows using GER, negative IFF values are added up over partners j:

$$IFF_{it}^{gross;in} = \sum_{j;IFF<0} IFF_{ijt}^{M} + \sum_{j;IFF<0} IFF_{ijt}^{X} \tag{19}$$

Net aggregation is a simple sum of all IFF values for i over j:

$$IFF_{it}^{net} = \sum_{j} IFF_{ijt}^{M} + \sum_{j} IFF_{ijt}^{X} \tag{20}$$

Prior to summing across partners for each reporter i, for both methods of aggregation, the IFF value is summed across commodities c first.

5 Findings

This section synthesizes key insights from the "atlas of misinvoicing" and provides examples of how the dataset can be used by interested stakeholders. Policy-makers can use these results to understand the scale of the problem in their jurisdiction, in addition to the major destinations and sectors where misinvoiced trade flows to. Results are reported as a dollar value of trade misinvoicing, as a percentage of GDP, and as a percentage of trade. The research question at hand should guide the choice of variable to represent trade misinvoicing as an explanatory variable. In many cases, a scaled value of trade misinvoicing (e.g., as a percentage of GDP) will be more appropriate than a dollar value.

This section proceeds as follows. First, global results are presented in order to glean a high-level understanding of the problem. Subsequently, the analysis zooms in to various country groups in order to demonstrate the potential of this dataset in understanding the sources, sinks, and sectors that are responsible for most trade misinvoicing.

5.1 Global results

The "atlas of trade misinvoicing" provides results for most countries in the world (167). To my knowledge, there is no publicly available dataset of misinvoicing estimates that has such broad country coverage.

Globally, the top 3 countries with the highest average annual gross outflows during the period 2000-2018 were the United States ($221 billion), Canada ($65 billion), and China ($59 billion). The magnitude of trade misinvoicing in the USA is much larger than trade misinvoicing in other countries. However, the USA had a GDP of $21 trillion in 2018 and its total trade (calculated as the sum of reported imports and exports) in 2018 amounted to $4.28 trillion. Reporting trade misinvoicing on a dollar basis may yield results that emphasize open economies with large volumes of trade, since in those countries there is more trade that can be misinvoiced.[31]

Therefore, trade misinvoicing estimates are presented as a percentage of countries' trade (the sum of their reported imports and exports), as displayed in Figure 3. Africa and Latin America tend to have higher trade misinvoicing as a percentage of trade, compared to Europe which has the least. The figure also highlights the extent to which trade is misinvoiced in Africa. Further analysis on Africa is undertaken in the following section.

The top 10 countries with the highest average gross outflows as a percentage of trade during 2000-2018 were Yemen (58%), Congo (55%), Tanzania (41%), Cambodia (23%), Côte d'Ivoire (20%), Trinidad and Tobago (20%), South Africa (18%), Angola (16%), Costa Rica (16%), and Azerbaijan (16%). The fact that the majority of those countries are developing should be a cause for alarm for policy-makers focused on poverty alleviation and sustainable development. It should be noted that though it may be a factor, the methodology adjusts

[31] This assumes that there is a limit to the extent that a given shipment can be misinvoiced. This may be correct − truly outrageous degrees of misinvoicing for a given shipment may risk detection by customs authorities.

for the poor quality of data reporting practices in countries through a variety of methods (e.g., censoring the dataset to observations where the observed trade gap is less than 100, removing statistical outliers, performing the reconciliation procedure that downweighs poor quality reports, etc.). Robustness checks were performed to verify that the threshold used for removing outliers did not significantly change the main results.

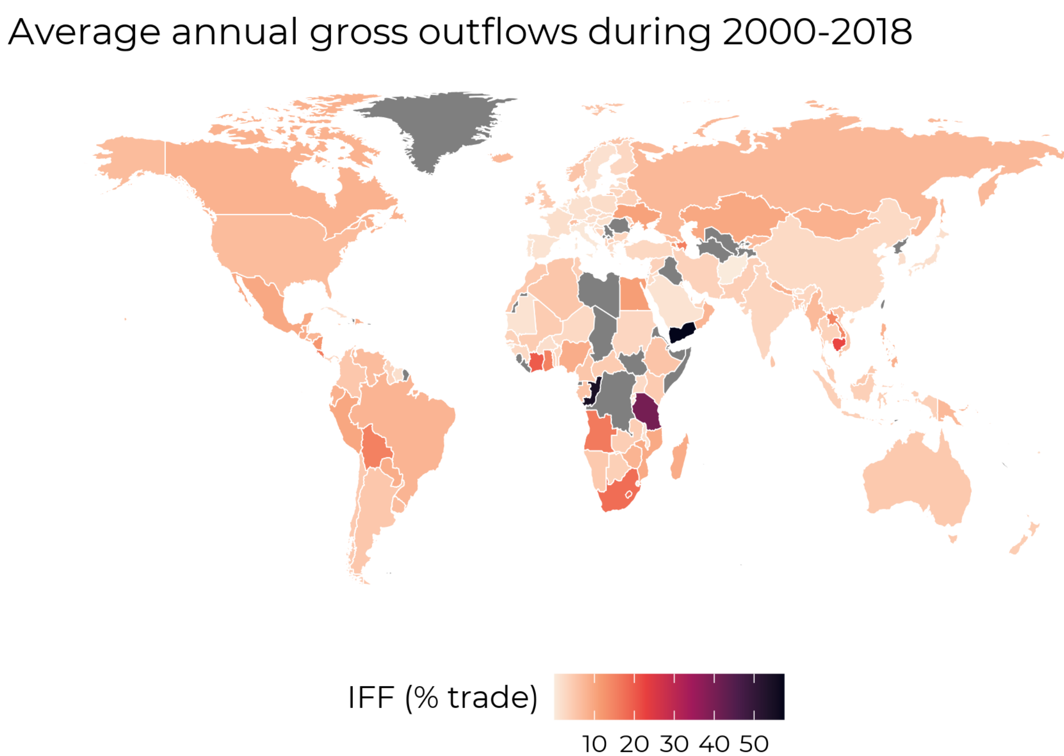

Figure 3: Average yearly gross outflows as a percentage of trade.

The deleterious impact of trade misinvoicing on domestic resource mobilization can best be understood by examining results as a percentage of countries' GDPs. Africa, eastern Europe, and central Asia experienced the highest average gross outflows as a percentage of GDP during 2000-2018. The top 10 countries on that basis were Congo (54%), Yemen (37%), Cambodia (21%), Trinidad and Tobago (19%), Tanzania (17%), Hong Kong (15%), Angola (15%), Côte d'Ivoire (14%), Singapore (13%) and Costa Rica (11%).

The dataset also permits identification of the greatest "sinks" for illicit flows, that is, countries which have the highest gross inflows (either through import under-invoicing or export over-invoicing). There is a negative and statistically significant (Spearman's $\rho = -0.58$; p-value < 0.01) correlation between a country's rank on the Financial Secrecy Index (FSI) – where the top rank corresponds to the most financial secrecy – and the amount of illicit inflows that it receives. The FSI ranks countries on various dimensions of financial secrecy and according to the scale of their offshore activities. Indicators of financial secrecy used in the index include the degree of information around the beneficial owner of an asset, the degree of transparency on legal entities and the extent to which it is available to the public, the integrity of tax and financial regulation, and finally how cooperative countries are with regards to international standards for financial disclosure. The top 5 countries on the 2018 edition of the FSI are, in descending order: Switzerland, the United States, Cayman Islands, Hong Kong, and Singapore. Figure 4 shows that the top 3 countries with the highest average gross inflows in the period 2000-2018 are among the highest ranked on the FSI. The Netherlands and Russia are number 14 and 29, respectively, on the FSI.

This reaffirms that financial secrecy is a scourge and that efforts to increase global financial integrity are a vital component of achieving the SDGs and building a global architecture that is supportive of sustainable development. Recognizing this priority, in 2019 the UN General Assembly assembled the panel on Financial Accountability Transparency and Integrity (FACTI).

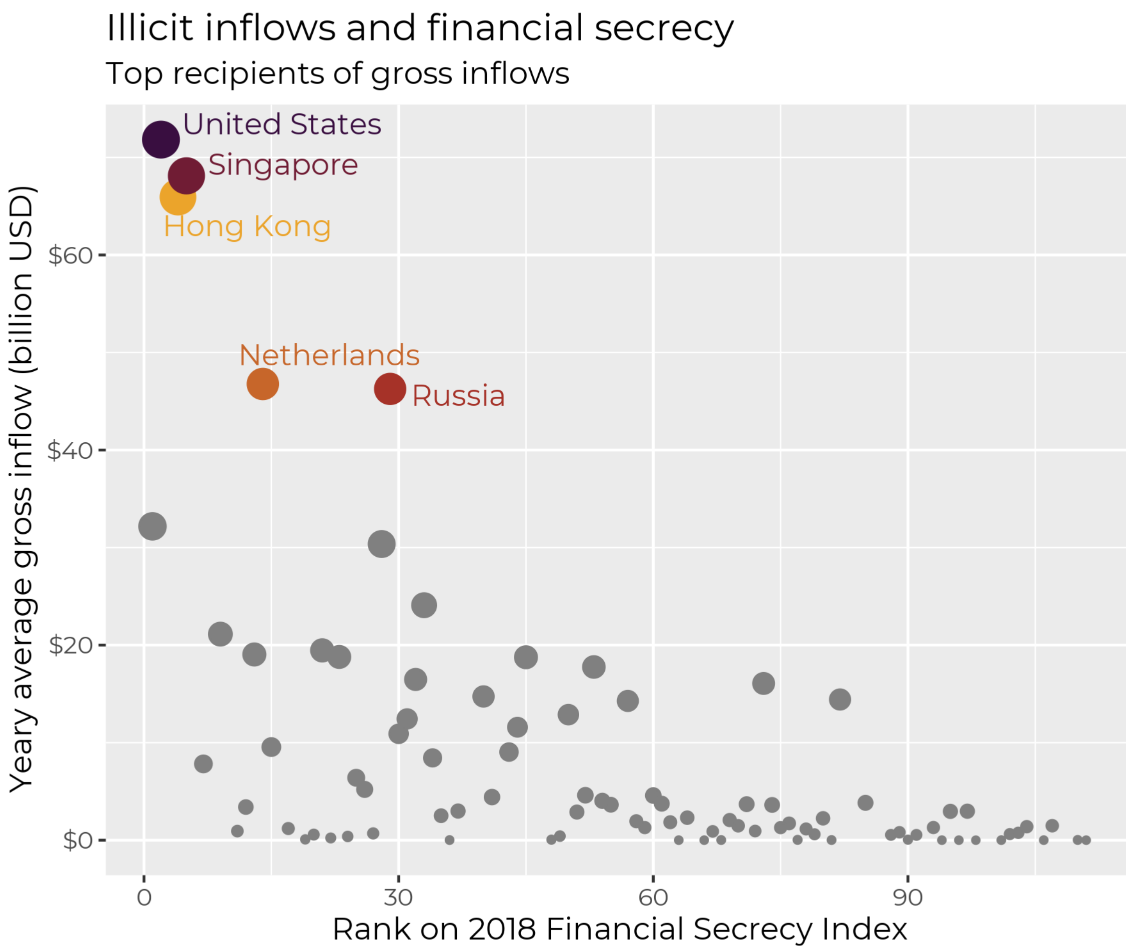

Figure 4: Association between financial secrecy and receipt of illicit inflows.

The underlying reasons for trade misinvoicing will vary by sector. Some sectors, notably natural resources, are more susceptible to misinvoicing that is used to finance conflict and to embezzle money from the state (Vézina, 2015; UNECA, 2017; Andreas, 2015). In other sectors, misinvoicing will primarily be explained by abuses of transfer pricing by multinational companies in order to book profits in lower-tax jurisdictions (UNECA, 2018a; Davies et al., 2018; UNECA, 2019; Tørsløv et al., 2018; UNECA, 2018b). This is likely to be the case in oligopolistic markets that are dominated by a few large multinational conglomerates, such as pharmaceutical products for example.

The Sankey diagrams in figures 5 and 6 provide an example of the sectoral breakdown of illicit financial flows. In each sector, the top 5 countries (by % of GDP) with the highest average gross yearly outflows during 2000-2018 are displayed on the left axis. The respective destinations of those illicit outflows are depicted on the right axis, with the width of segments proportional to the dollar value of the illicit flow.

This is an example of how this atlas of illicit financial flows can be used to study the sinks and sources for each of the 99 sectors in the Harmonized System. The potential for discovery of additional insights is large and will be a matter for future research.

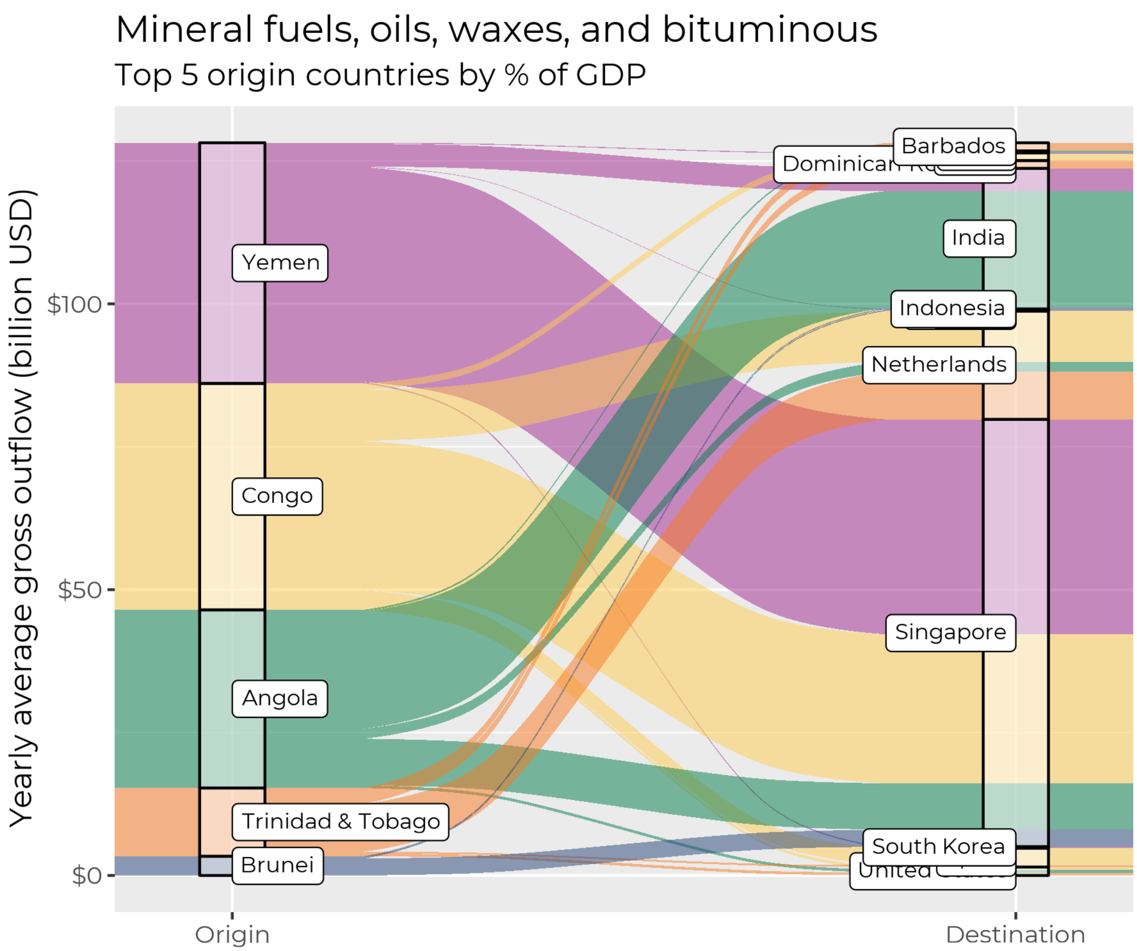

Figure 5: Destination and magnitude of flows originating from the top 5 countries in mineral products.

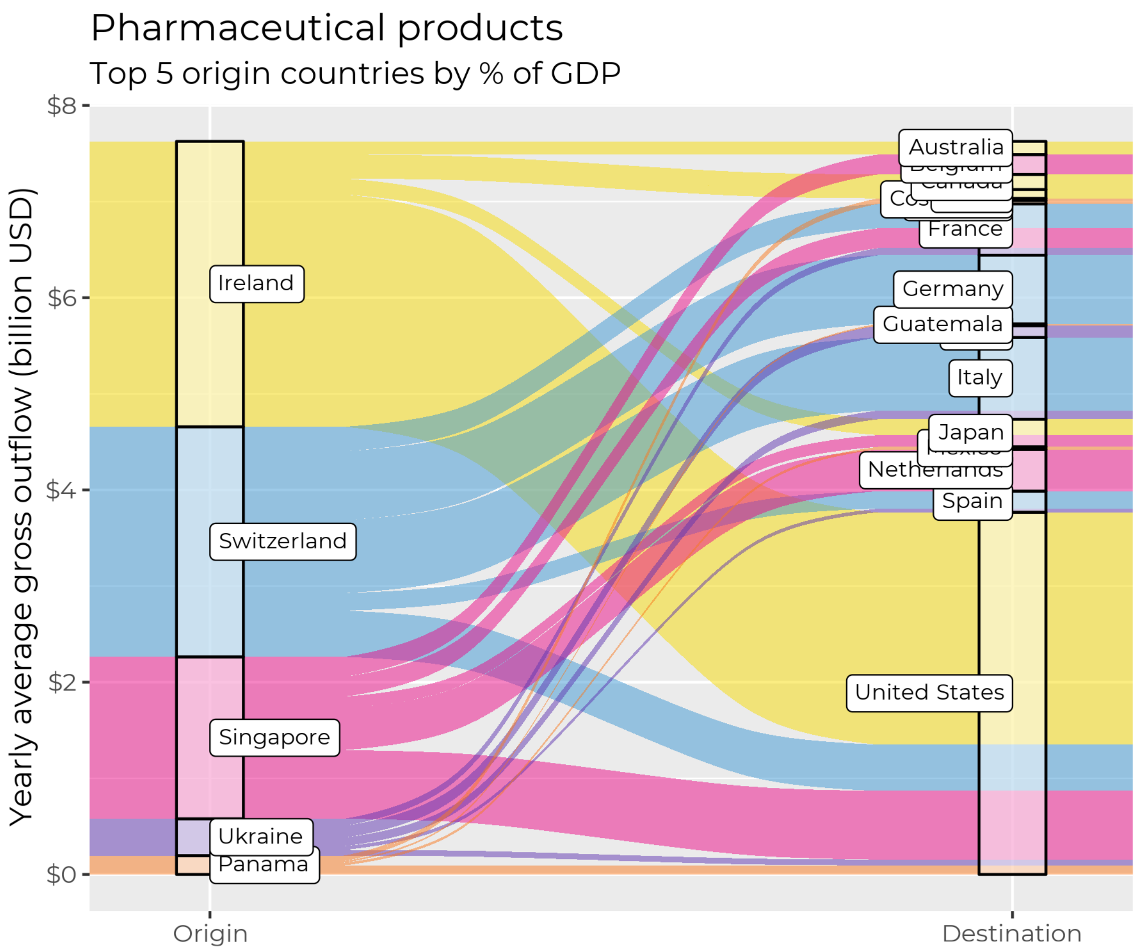

Figure 6: Destination and magnitude of flows originating from the top 5 countries in pharmaceutical products.

5.2 Results for Africa

Given that African countries feature prominently in the top conduit countries for illicit outflows (both as a percentage of GDP and of trade), this section turns to analyzing the extent and patterns of misinvoicing in Africa.

Figures 7 and 8 display the yearly evolution of gross and net financial outflows from the continent, both as a percentage of GDP and as a percentage of trade. Africa had net illicit inflows in the early 2000s but has experienced illicit outflows in the latter half of the 2010s. This suggests that gross illicit inflows are a large component of trade misinvoicing. As discussed earlier, those inflows are untaxed, invisible to governments, and can be used to strengthen corrupt elites and finance organized crime and terrorism. The magnitude of misinvoiced trade in the continent is around 10% which is broadly consistent with, though more conservative than, findings from Global Financial Integrity who estimate that the percentage of Sub-Saharan Africa's trade with advanced economies that was misinvoiced during 2006-2015 was on average 17.4% for gross outflows and 15.2% for gross inflows (Salomon, 2019, p. 2).

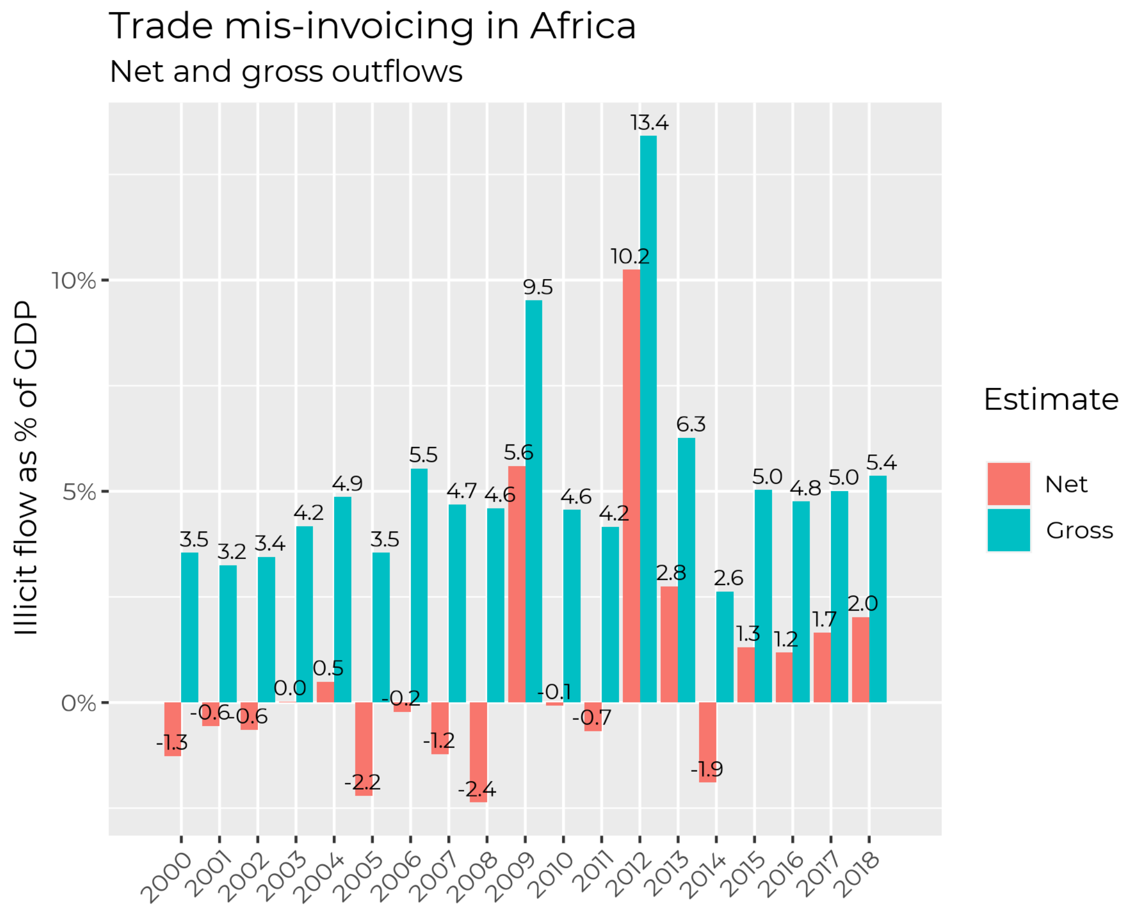

Figure 7: Net and gross outflows in Africa as a percentage of GDP.

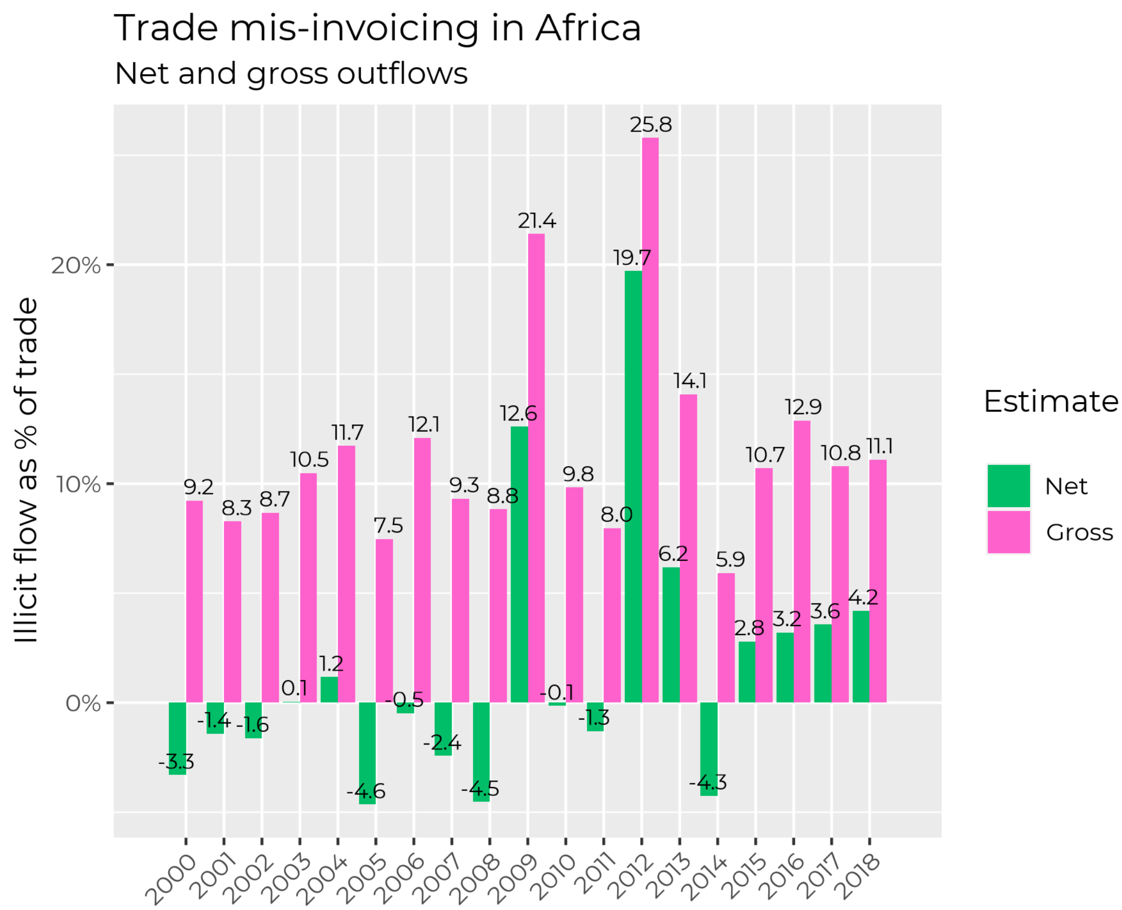

Figure 8: Net and gross outflows in Africa as a percentage of trade.

Next, the "atlas" dataset provides a sectoral breakdown of illicit flows on the continent, as illustrated in Figure 9. The overwhelming amount of gross outflows occurs in the natural resource sector. The extent to which natural resources can contribute to a resource curse, enable conflict, and hamper development has been well-documented and debated (see, e.g., Dunning (2008); Ross (2015)). Conventional accounts of the resource curse hold that windfall profits from natural resources can cause Dutch disease through an appreciation of the real exchange rate and can entrench the power of unaccountable elites (Ross, 1999; Oliver et al., 2017). These results provide additional insights on the resource curse by suggesting that windfall profits are not the only mechanism of harm, and that illicit outflows through trade misinvoicing will exacerbate capital flight and deplete governments' fiscal reserves.

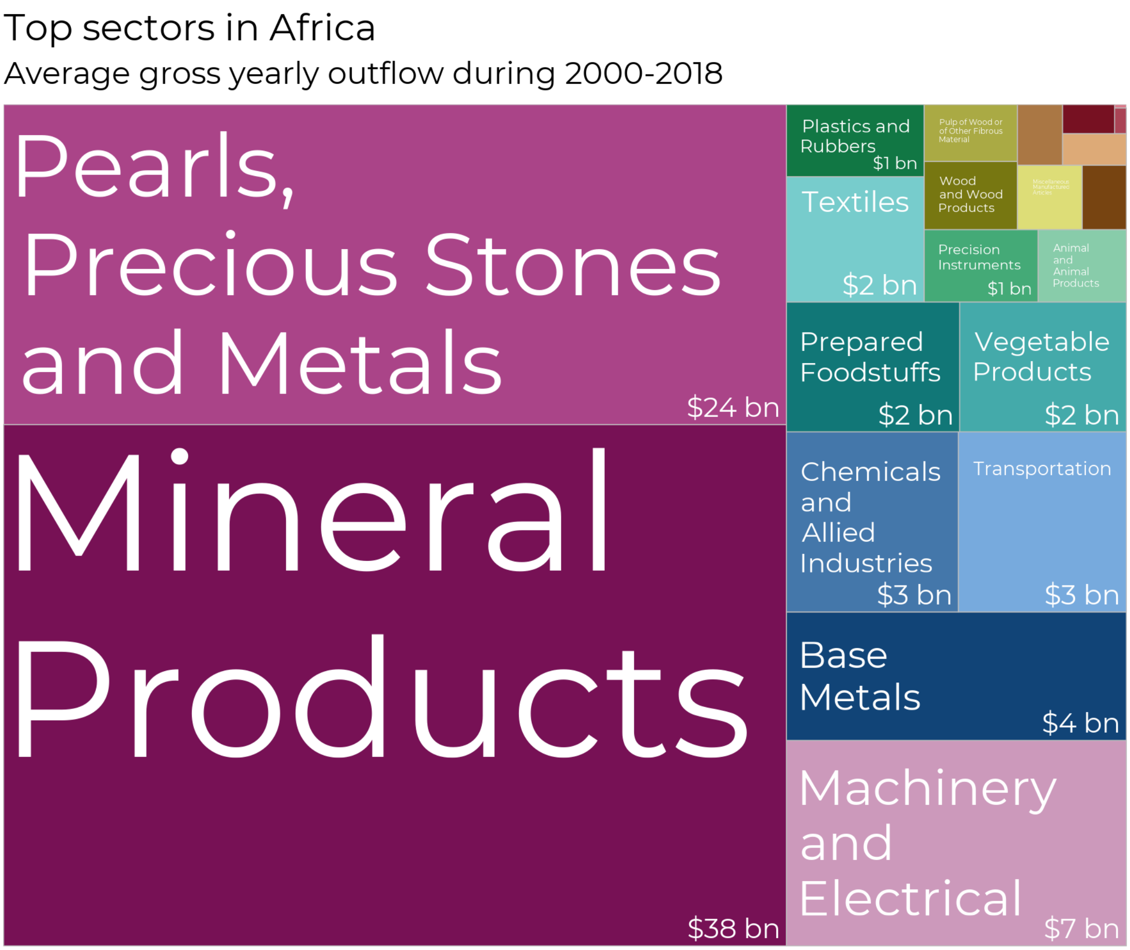

Figure 9: Top sectors in Africa for outflows during 2000-2018.

The data also reveal that mineral products are the main sources of misinvoicing. This is in line with the High Level Panel on Illicit Financial Flows from Africa (2015) which found that oil, precious metals, and minerals were the leading source of trade misinvoicing (via re-invoicing) from Africa from 2000 to 2010, followed by ores and electrical machinery and equipment. ESCWA (2018) excludes the main sector used here (Harmonized System classification 27, which includes mineral products) from its sectoral disaggregation but finds that machinery and electrical machinery are the main sources of illicit financial flows in the Arab region.

The "atlas" estimates that the natural resources sector is by far the most misinvoiced across the continent, yielding gross outflows of $62 billion annually on average. This is particularly consequential given that 46 out of the 54 countries on the continent are classified as highly dependent on the export of primary commodities (UNCTAD, 2020). Moreover, the extractives industry is characterized by a high degree of market concentration due to the capital-intensive activities involved in the large-scale extraction of minerals and other natural resources, and as such the market is dominated by Multinational Enterprises (MNE) who yield a considerable amount of influence over African governments. MNEs have the technical expertise to circumvent domestic laws, have the leverage to negotiate tax regimes that are advantageous to them but erode the tax base of national governments, and possess the market power to manipulate prices and other costs along the commodity value chain (UNCTAD, 2016, 2020; UNECA, 2017, 2019).

It is useful to examine the sources and sinks of illicit outflows in the top two sectors: mineral products[32] in Figure 10 and pearls, precious stones and metals[33] in Figure 11. The figures display the top 5 destinations of illicit outflows for the top 5 African countries in each sector (as a percentage of GDP). The top origin countries in the sector of pearls, precious stones and metals include large diamond producers such as Botswana and South Africa. Though Botswana is often heralded as a country that has managed to avoid the resource curse by entrusting the revenues to a sovereign wealth fund (Iimi, 2007; Sarraf and Jiwanji, 2001), the results suggest that revenues still escape the government through trade misinvoicing. These data can thus contribute to the evidence base for initiatives that aim to strengthen governance in the natural resource sector (UNECA, 2017).

[32]This sector includes HS chapters 25, 26, and 27 which correspond to “Salt; sulphur; earths and stone; plastering materials, lime and cement”, “Ores, slag and ash” and “Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes”, respectively.

[33]This corresponds to HS chapter 71. The full description is “Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal and articles thereof; imitation, jewellery; coin”.

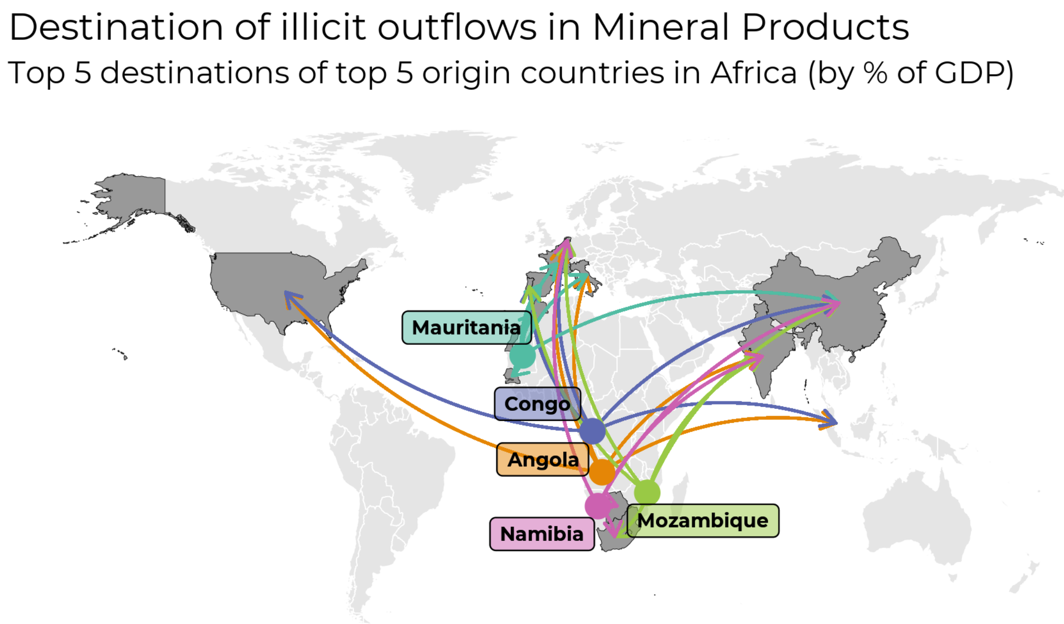

Figure 10: Destination of outflows in mineral products (highest sector).

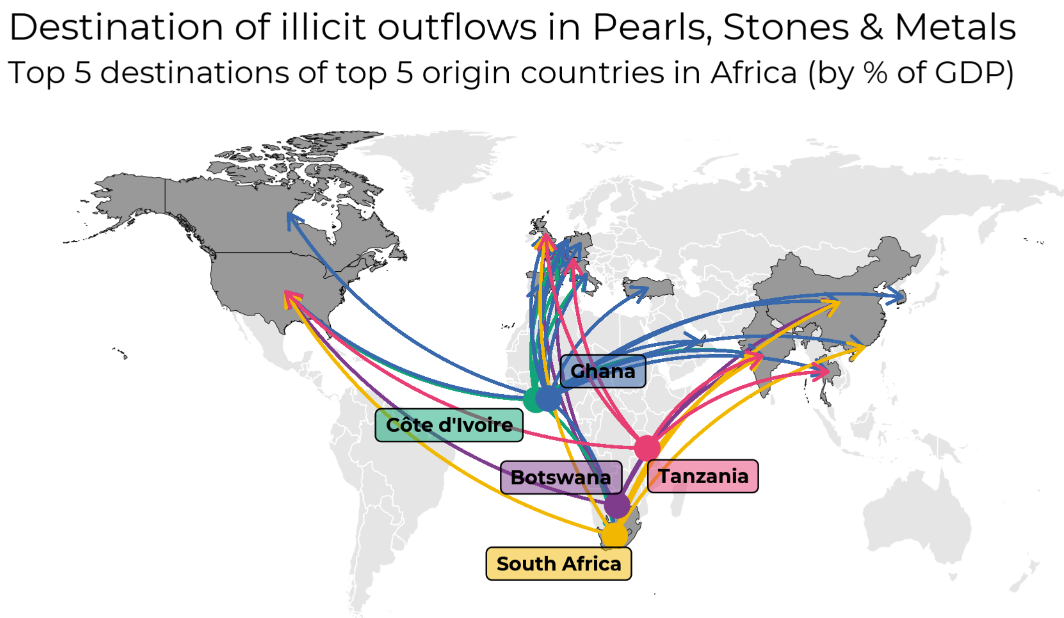

Figure 11: Destination of outflows in pearls, stones and precious metals (second highest sector).

5.3 Results for low and lower-middle income countries

Since IFFs pose significant challenges to the financing of development in poor countries, this section presents results for the 19 low income and 44 lower-middle income countries in the "atlas" dataset (classified according to the latest World Bank classification in July 2020). Low income countries are defined as those with a GNI per capita of $1,035 or less in 2019, and lower-middle income countries are those with a GNI per capita between $1,036 and $4,045.

Figure 12 presents yearly misinvoicing for low and lower-middle income countries in terms of gross outflows, gross inflows, and net flows, and further breaks down gross flows by transaction type. Negative values represent illicit inflows. Illicit outflows (inflows) occur through import over-invoicing (under-invoicing) and export under-invoicing (over-invoicing). The fact that net flows are much smaller can be explained by the fact that the LMIC group represents a large set of countries and that these include large sinks such as India, the Philippines and Nigeria. Net flows tend to be negative (indicating net illicit inflows to the group as a whole) in most years, except for large spikes in net outflows in 2009 and 2012.

The amount of misinvoicing in imports is slightly larger than the misinvoicing in exports. This might be due to the fact that misinvoicers have greater control in falsifying import invoices than export invoices.

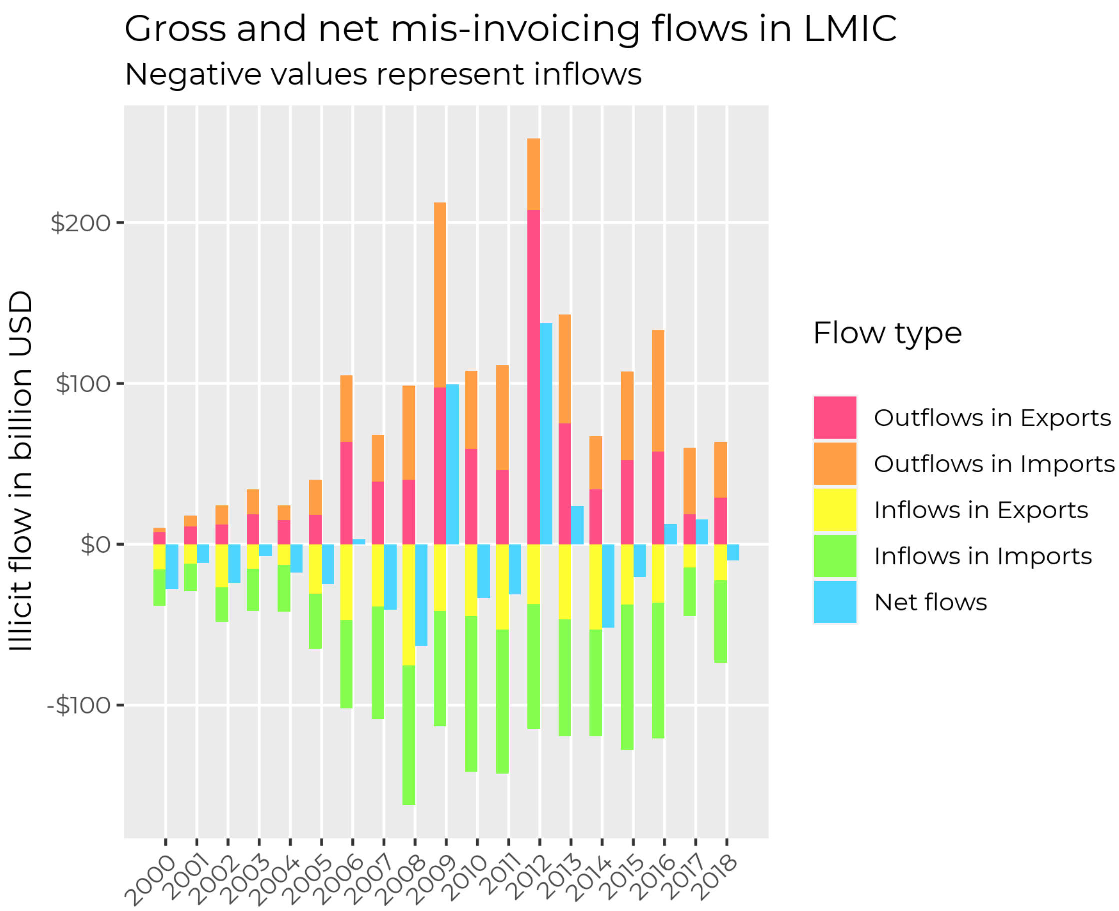

Figure 12: Breakdown of illicit outflows and inflows by transaction type.

The large discrepancy between gross and net flows is an interesting finding. This suggests that there are significant flows between low and lower-middle income countries (which would tend to increase gross outflows, but not net outflows), or that certain countries experience both substantial inflows and outflows, or that there is substantial misreporting of the name of the partner country or commodity, which would tend to increase gross outflows but not net outflows (as long as a shipment is recorded in trade data, incorrect reporting of partner country or commodity would lead to an apparent illicit outflow towards the true partner country and an inflow from the incorrect partner country of equal size, which could cancel out in aggregate net national statistics).[34]

Figures 13 and 14 display the top sources and sinks for illicit flows (as a percentage of GDP) in low and lower-middle income countries.

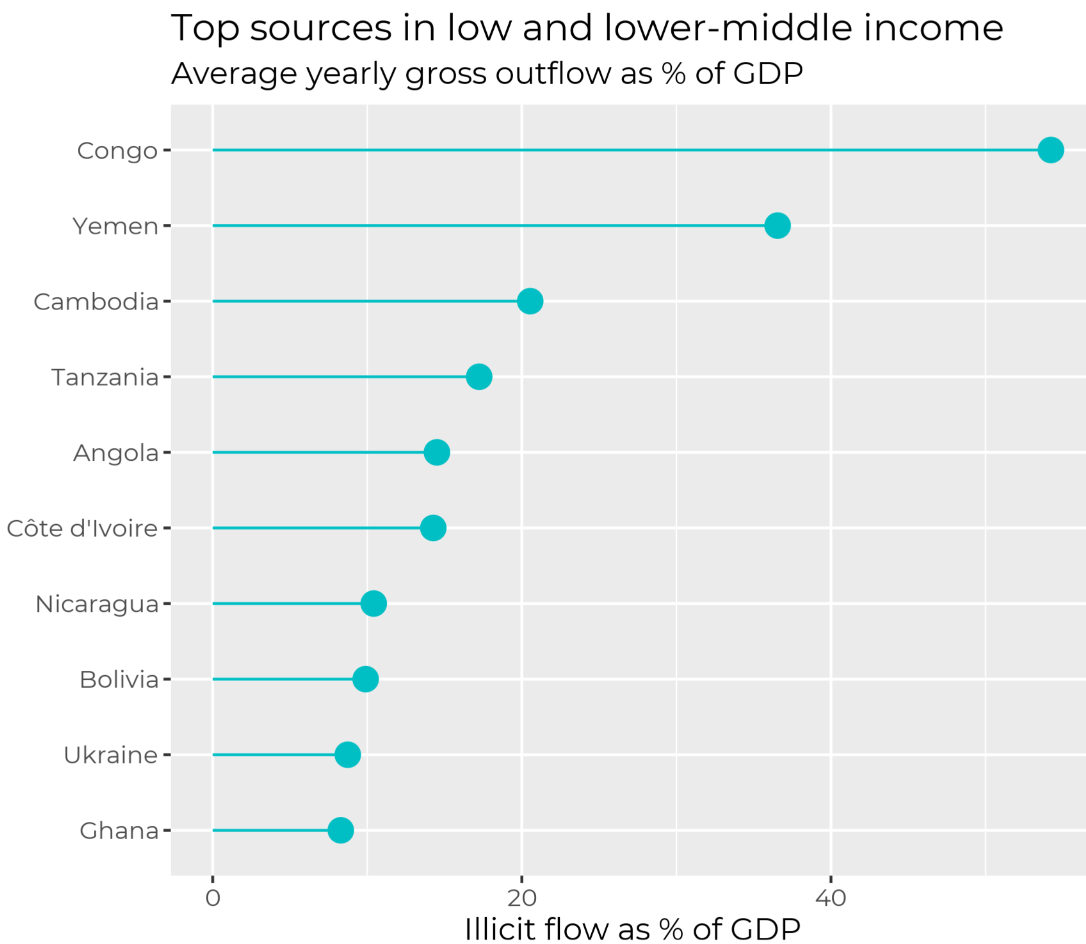

Figure 13: Top 10 sources of illicit outflows by percentage of GDP.

[34]As noted above, it is unlikely that misreporting of commodity codes would have a significant impact on the estimates, since the "atlas" uses data at the 2-digit level, and while customs officers may be confused about the specific commodity code that a product falls under, this would seem unlikely to occur with the broad categories used at 2-digit level.

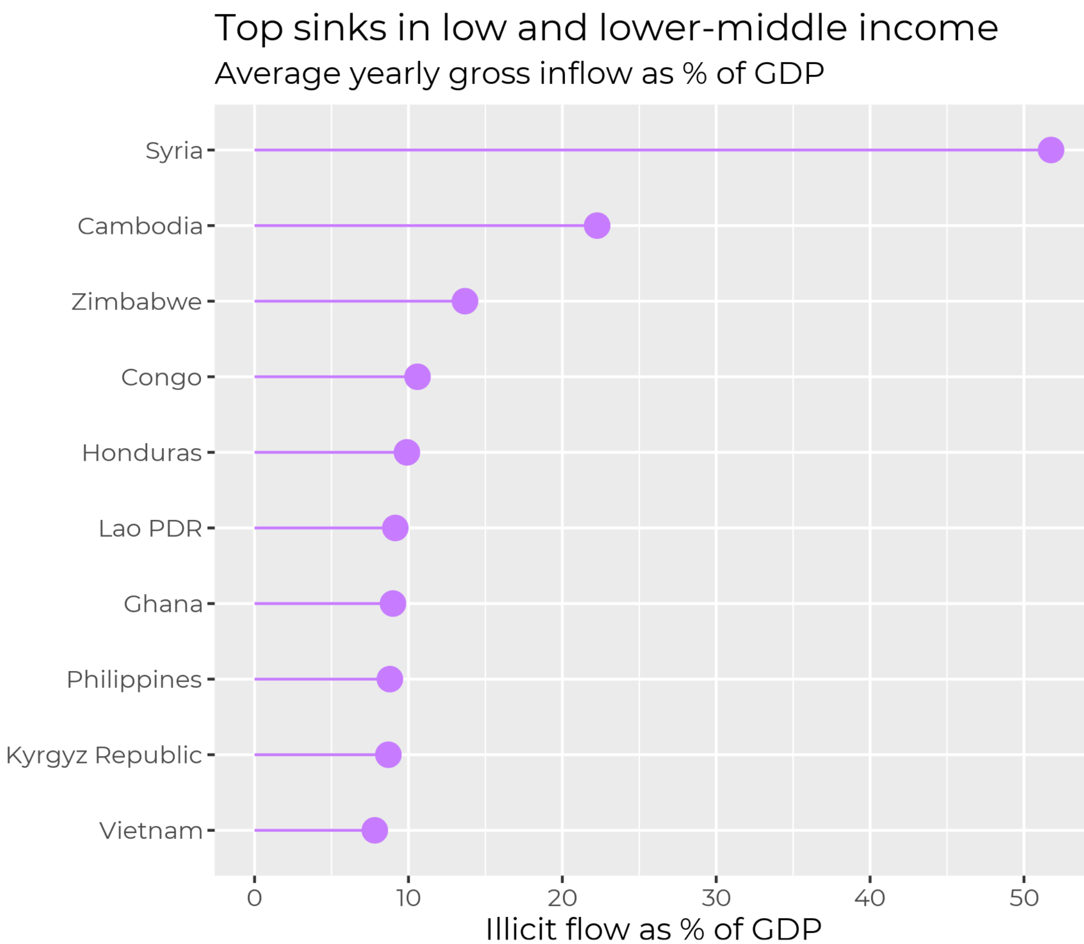

Figure 14: Top 10 sinks of illicit inflows by percentage of GDP.

Figure 15 provides the sectoral breakdown for top source countries using the Standard International Trade Classification (SITC) sector. While mineral products account for a large part of outflows in low and lower-middle income countries, there is also a large amount of misinvoicing in manufactured goods.

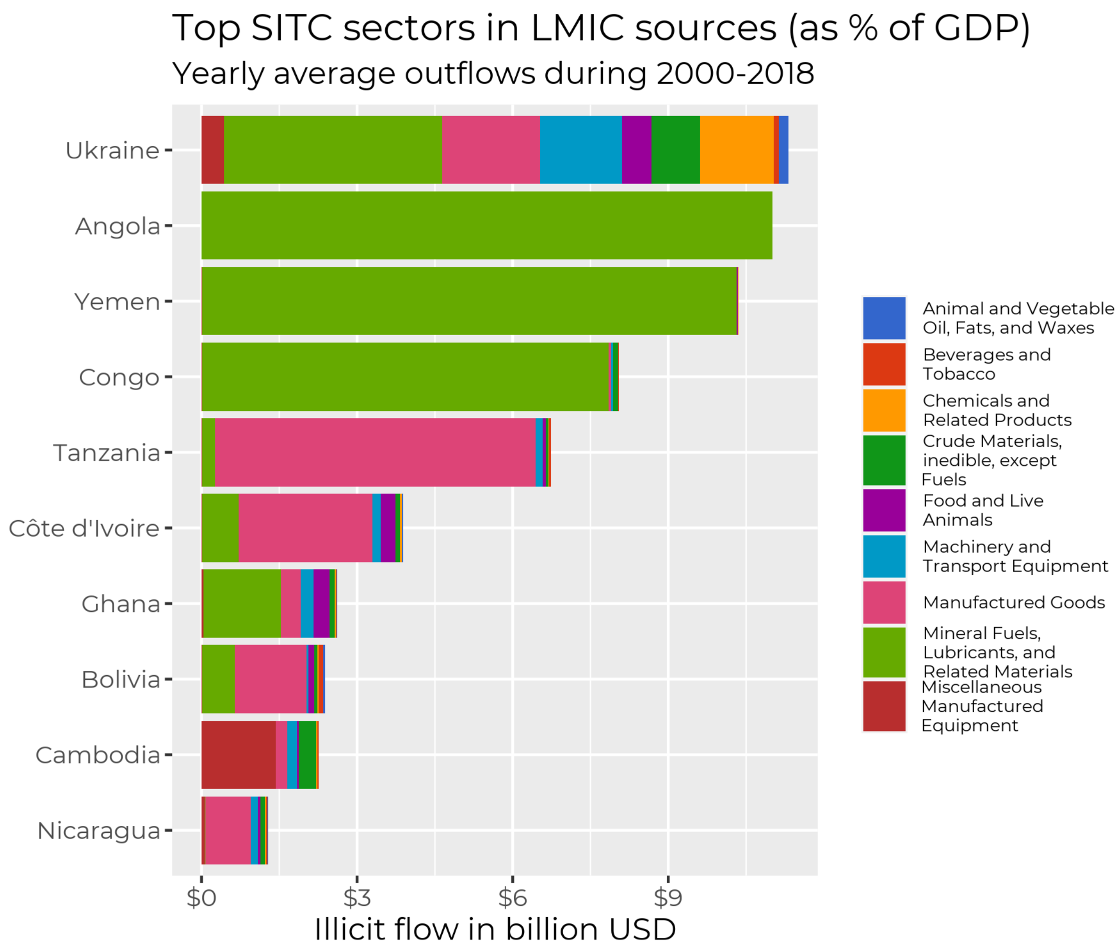

Figure 15: Sectoral breakdown of outflows in top 10 countries (as % of GDP).

The distributional implications of trade misinvoicing are also important to consider. According to Figure 16, most of the outflows from low and lower-middle income countries accrue to rich countries that have a GNI per capita greater than $30,000. Furthermore, within the lower tranche of the LMIC classification (below $2,000), outflows tend to go to comparatively poorer countries than outflows from the higher tranche of LMIC countries (above $2,000).

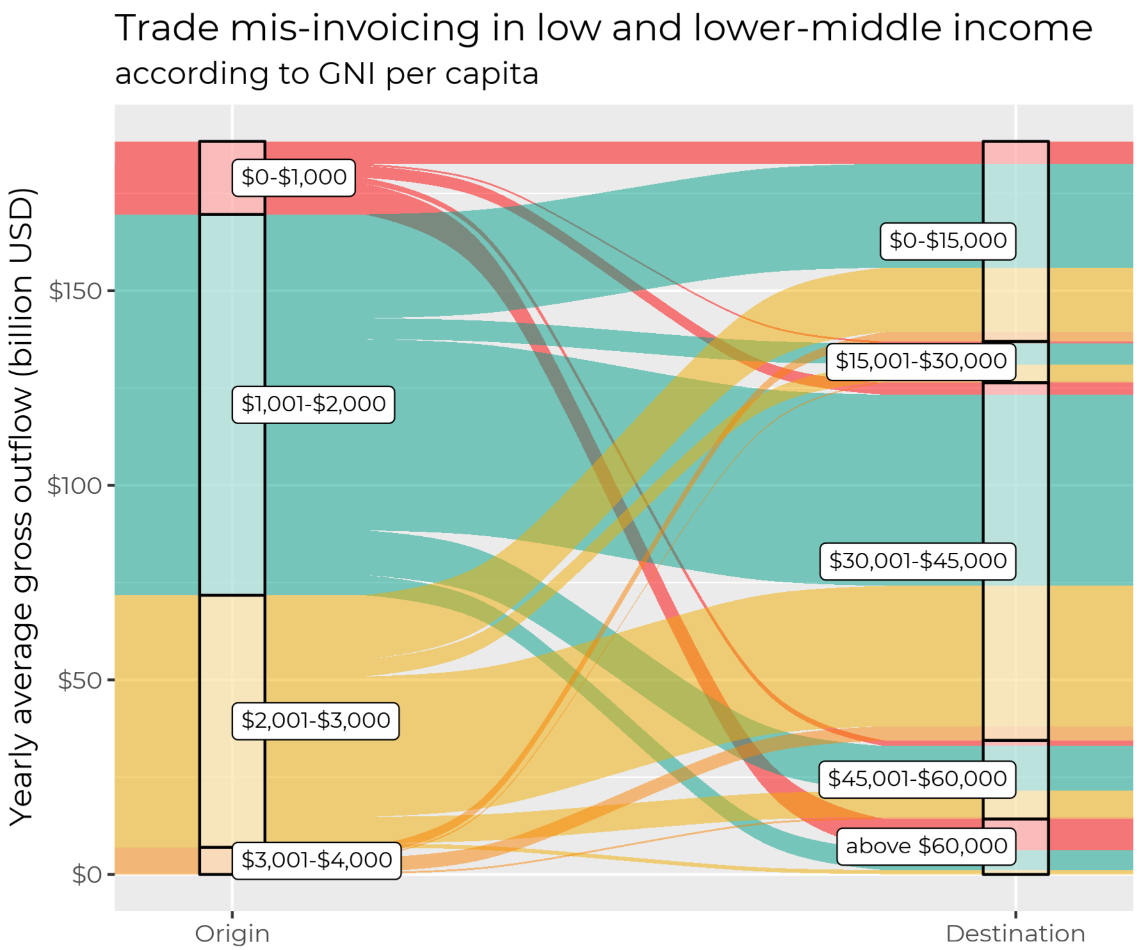

Figure 16: Breakdown of outflows from low and lower-middle income countries by GNI per capita.

Finally, Figure 17 displays the top destinations of outflows from low and lower-middle income countries. This is a mixed group which includes countries that are trading hubs, emerging economies, those that have a high degree of financial secrecy, and those that have a high presence of multinational companies. Countries that have many multinational corporations may be a significant destination for illicit financial flows that represent repatriated profits. As noted earlier, multinational corporations frequently use trade misinvoicing to transfer finance between parts of their multinational group located in different countries in order to evade fiscal and regulatory constraints.

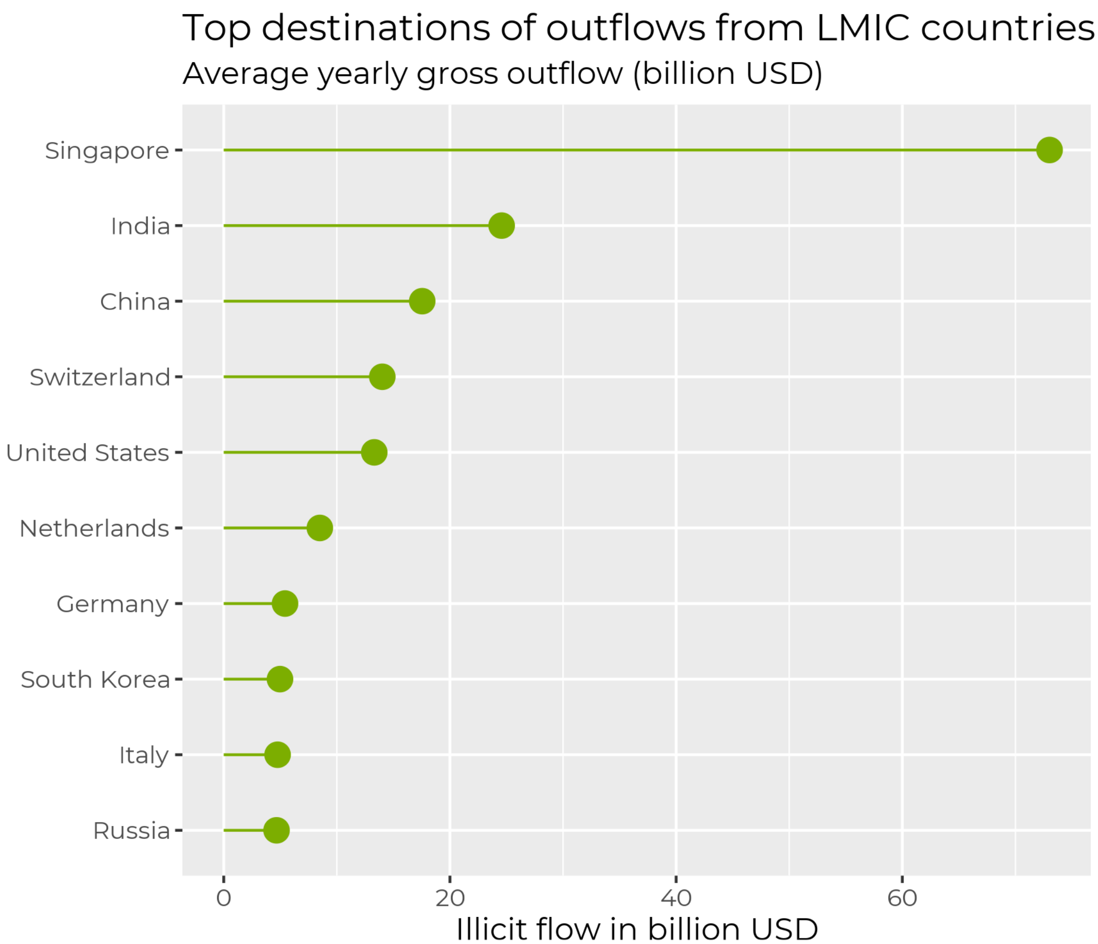

Figure 17: Top destinations of outflows from low and lower-middle income countries.

6 Discussion

The methodology of the "atlas of misinvoicing" does, of course, carry limitations. The estimates presented here are likely to be an underestimate of the true extent of the phenomenon of trade misinvoicing. First, they do not cover misinvoicing of the trade in services. Second, the method will not pick up misinvoicing where the distortion is repeated consistently at export and import (so-called "same-invoice faking" – see Kar (2010)). In particular, the mirror trade gaps approach will not capture when the importer and exporter collude at both ends of the transaction to submit over-valued invoices, and so the resulting mirror declarations match (World Customs Organization, 2018). For example, an importer can create a secret fund abroad to evade taxes or domestic financial controls by creating a subsidiary shell company in a foreign country. The importer can then remit an over-valued payment to the exporter by depositing the funds into the bank accounts of the (foreign) exporting company's shareholders. As a shareholder of the shell company exporter, the importer can then withdraw the illicit proceeds in small amounts at a time in ATMs in their country (World Customs Organization, 2018), a process known as "smurfing".[35] Third, using a higher level of commodity aggregation will likely result in "within-sector" netting which would underestimate the extent of misinvoicing. On the one hand, the methodological choice of using a higher level of commodity aggregation (at the 2-digit HS code) rather than more disaggregated commodity data such as the 4- or 6-digit codes is justified to avoid any false positive identification of misinvoicing due to genuine mistakes on how to classify a certain good when many similar options exist. However, the trade-off is that the higher level of aggregation will cancel out some over-invoicing of products with the under-invoicing of other products if they both fall under the same HS chapter (Kravchenko, 2018), and thus the method will miss genuine cases of misinvoicing. As a result, the estimates presented here are conservative and should be interpreted as a lower bound of the true extent of illicit financial flows from trade misinvoicing.

Moreover, the controls for delayed shipment arrivals and asymmetric reporting of re-exports might not be completely adequate, since the method assumes a linear relationship, and these phenomena are likely to have different effects across countries. However, the approach of econometrically controlling for these effects has the advantage of not requiring data on the quantities or weights being shipped (where the data coverage in Comtrade is much more scarce than for prices). Errors in trade data that are not corrected by the adjustments may also negatively affect the quality of the estimates, as might price fluctuations during shipment (Forstater, 2016) – though, errors should have only a minimal effect on the net estimates, since there would be errors both in estimating inflows and outflows which would tend to cancel each other out in the aggregate.

The paper offers several innovations by relaxing many of the existing (and sometimes implicit) assumptions in the literature. First, transportation and freight costs are no longer assumed to be a constant value; they are estimated econometrically, in a way that controls for trade misinvoicing that might have been missed by previous estimates of transport costs. Second, instead of assuming that declarations from developed economies are more accurate than declarations from poor countries, the relative trustworthiness of country declarations is empirically determined through the harmonization procedure. Importantly, the paper does not directly equate observed trade irregularities with trade misinvoicing. Nor does the paper assume that only the portion of trade discrepancies that *are* explained by predictors of illic-

[35] This type of manipulation would only be detectable by exchanging information on the ultimate beneficial ownership of the traders, a proposed policy initiative in the fight against IFFs which is the subject of ongoing political negotiation.

itness are related to trade misinvoicing. Rather, the "residual" approach of the paper makes the assumption that trade gaps that cannot be explained by non-illicit or benign reasons are the result of either deliberate misinvoicing or statistical noise.

The coefficient estimates for the estimated licit and illicit margins should be interpreted cautiously and are likely to be correlational, and not causal. By not elucidating the causal mechanisms of observed trade gaps, this complicates the partition of the trade gap into its respective licit and illicit components. Moreover, the act of partitioning assumes that predictors of discrepancies can be attributed to either legitimate or illegitimate reasons, but not both at the same time. However, the estimand of interest here is not the causal effect of those predictors on the trade discrepancies; rather, it is the population quantity of the amount of trade misinvoicing. In that sense, the respective *groups* of coefficient estimates are of interest because they provide marginal effects that hold constant the other type of predictors. But individual coefficient estimates are not directly used to ascribe illicit intent to an observed trade gap. Different specifications of the gravity models that take advantage of the panel structure of the data could also be explored to increase the plausibility of causal identification of the coefficients, but there are some difficulties. Including country-time fixed effects as is sometimes recommended in the gravity literature (e.g., Yotov et al. (2016)) would absorb the variation in other predictors of interest to illicit flows that are country-specific and vary across time, such as the governance variables or many additional potential variables relating to country institutions and national policies. Future work should be directed towards conducting further sensitivity checks about the robustness of the results to the changing of assumptions and predictors used in the methodology, including the treatment of outliers, and the inclusion of additional predictors of illicit determinants.

There are two broad interpretations of the concept of "illicit financial flows" in the literature: a narrow, legalistic one where IFFs are defined as international transfers of funds that were or are illegally obtained, transferred or used; and a broad definition, which understands such flows to be any international transfers of wealth that are harmful to development (UNECA, 2018a; Blankenburg and Khan, 2012; Cobham and Janský, 2020). Of course, this begs the bigger question of what is desirable, and the decision as to what counts as an illicit financial flow becomes political, linked to what form of development one considers to be positive; and it therefore cannot be easily answered by technocrats. But the question of what illicit financial flows are, and to what extent we should tackle them, was political to begin with anyway – it must be, since, as this paper has shown, it has profound consequences for the international distribution of wealth, creating winners and losers, and it will therefore sharply divide opinion along political lines. Nevertheless, this paper hopes to provide a significant contribution to the discussion on trade misinvoicing and its likely extent. Moreover, the estimates presented here still find that the magnitude of IFFs through trade misinvoicing is substantive, broadly in line with the findings of other estimates. This suggests that existing estimates of trade misinvoicing are not, as some authors have suggested, an artefact of these statistical phenomena. Instead, the results support the argument that trade misinvoicing is real, substantial, and the conduit for hundreds of billions of dollars of illicit financial flows every year, suggesting that combating illicit financial flows should be an urgent priority for policy-makers.

7 Conclusion

This paper has presented the "atlas of trade misinvoicing", an original dataset of estimates for 167 countries during 2000-2018 that provides both broad country coverage and disaggregated estimates by year and by sector. Academics might find the dataset useful as a new dependent variable or might wish to use estimates of illicit flows as an additional control variable in econometric work looking at globalization, investment, and development.

Moreover, the paper offers a new methodology that seeks to mitigate some of the main concerns of the literature on trade misinvoicing estimates. In particular, the method adopts both a "residual" and a "harmonization" approach that adjusts for sources of illicit and non-illicit discrepancies in trade data and for the quality of a country's declaration in order to provide a more accurate estimate.

This paper demonstrates how the "atlas" can be used in further analysis by identifying leading sources, destinations, and commodities involved in trade misinvoicing. Natural resources lead the commodities affected by trade misinvoicing in developing countries, while the main destinations appear to be either countries with a high level of financial secrecy or countries in which many multinational corporations are based. Illicit financial flows deplete government revenues, weaken governance, and erode state institutions. Inflows are also detrimental to development since they are untaxed and invisible to governments. The estimates presented here are conservative and should be interpreted as a lower-bound of possible misinvoicing. This paper provides empirical confirmation that illicit outflows and inflows are pervasive across developing countries. In order to meet the challenge of the 2030 Agenda for Sustainable Development and to realize the SDGs, reducing illicit financial flows will be crucial for domestic resource mobilization.

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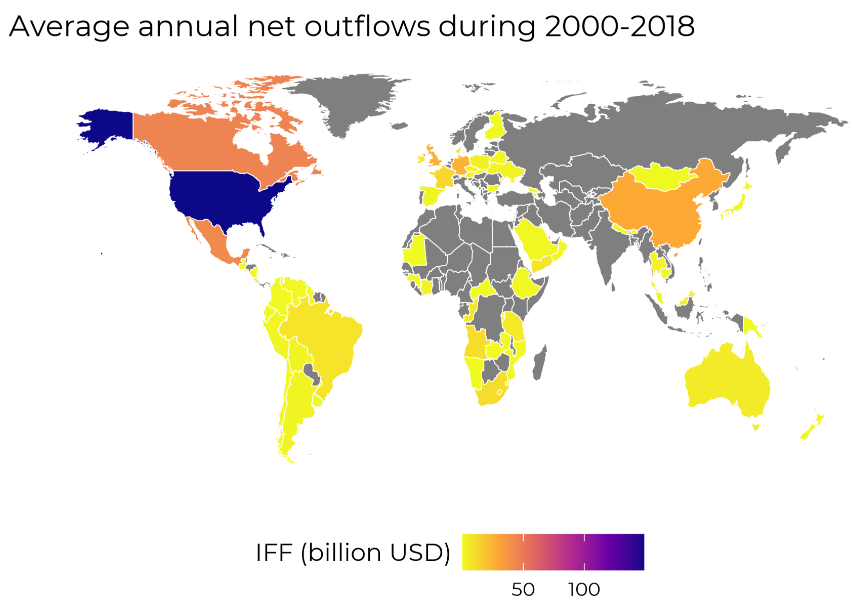
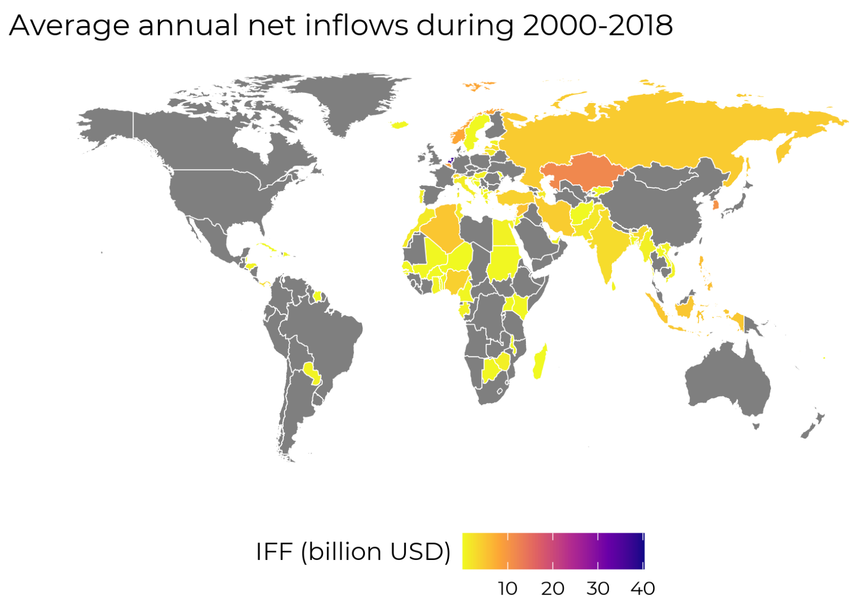
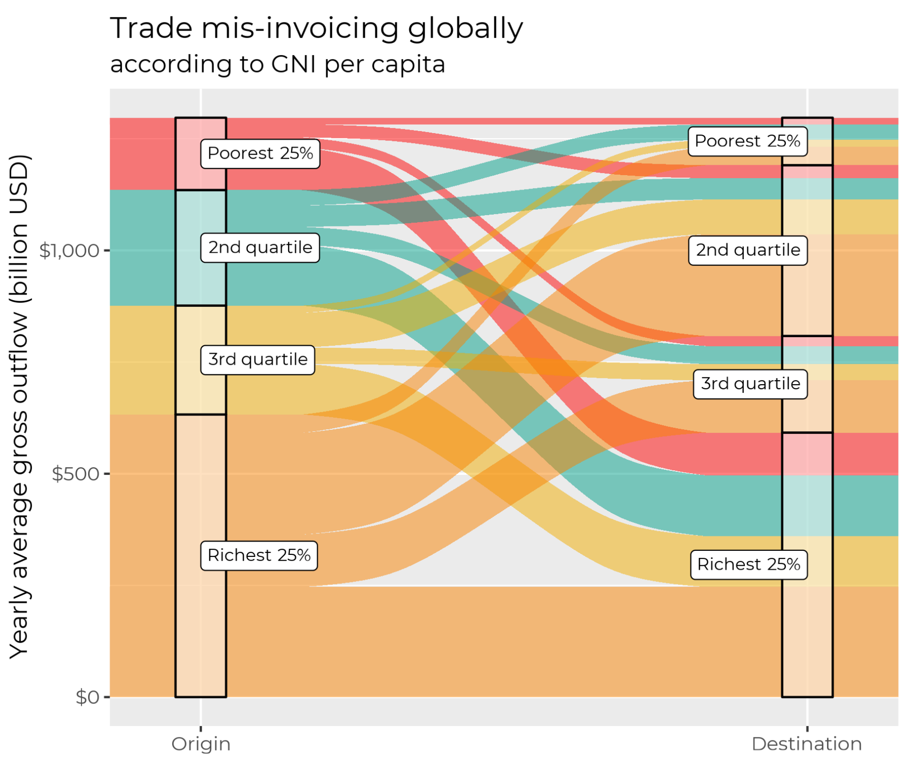
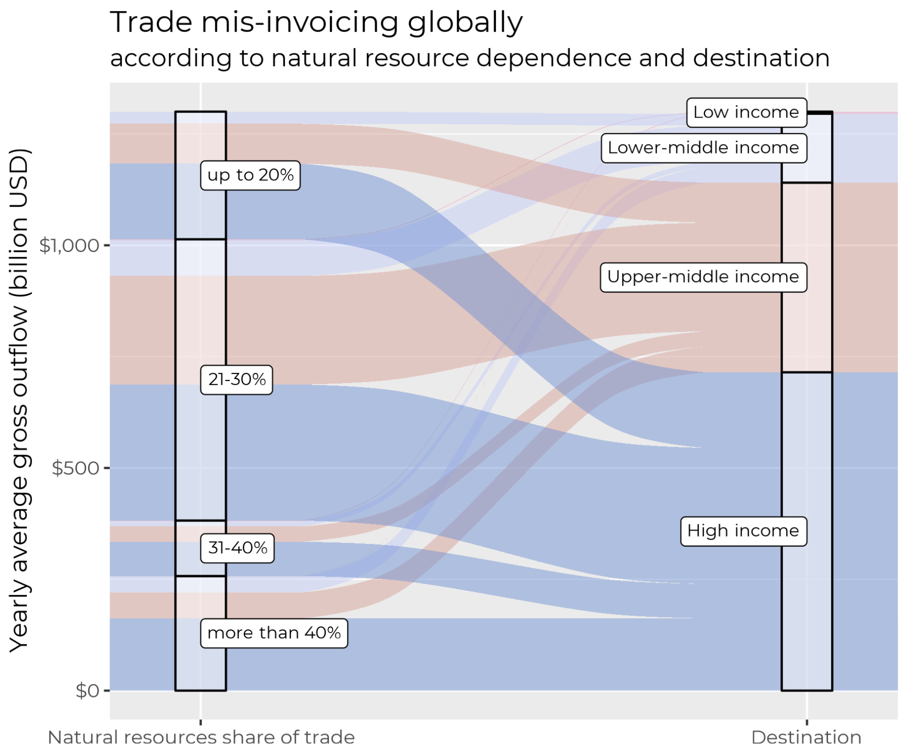
Appendices

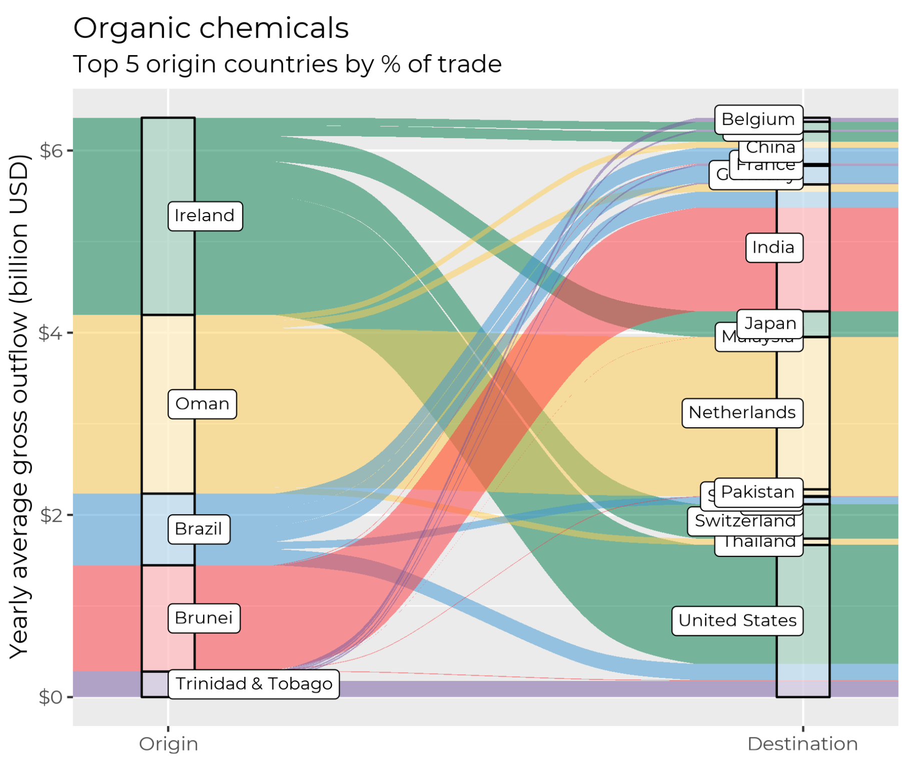
A Selected figures from the “atlas”




Average annual net inflows during 2000-2018
IFF (billion USD)
10
20
30
40

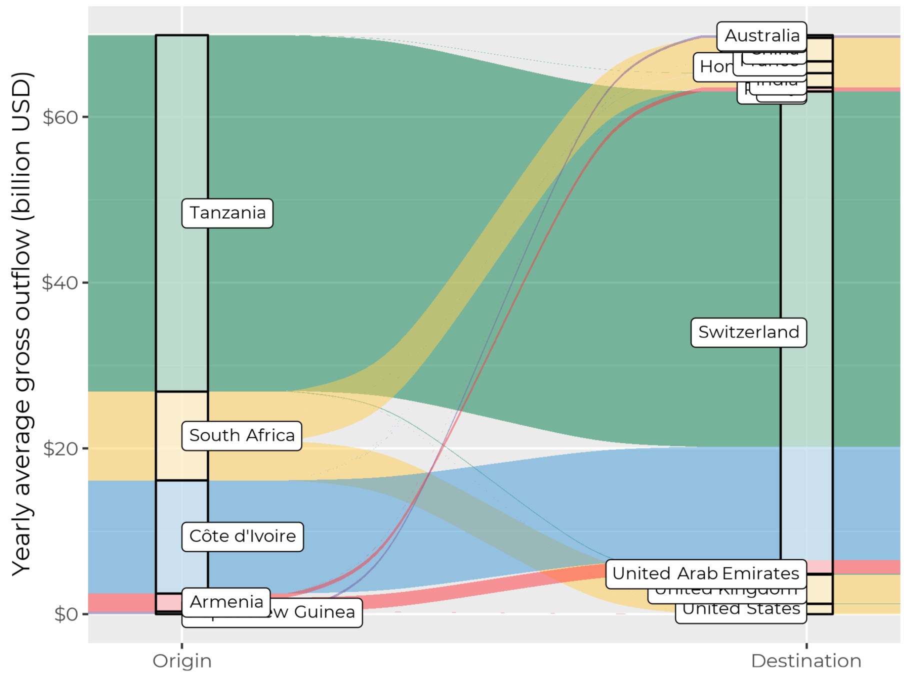

Trade mis-invoicing globally
according to GNI per capita
Yearly average gross outflow (billion USD)
$1,000
$500
$0
Poorest 25%
2nd quartile
3rd quartile
Richest 25%
Poorest 25%
2nd quartile
3rd quartile
Richest 25%
Origin
Destination


Trade mis-invoicing globally
according to natural resource dependence and destination
Yearly average gross outflow (billion USD)
$0
$500
$1,000
up to 20%
21-30%
31-40%
more than 40%
Low income
Lower-middle income
Upper-middle income
High income
Natural resources share of trade
Destination


Organic chemicals
Top 5 origin countries by % of trade
Yearly average gross outflow (billion USD)
$0
$2
$4
$6
Ireland
Oman
Brazil
Brunei
Trinidad & Tobago
Belgium
China
France
India
Japan
Netherlands
Pakistan
Switzerland
Thailand
United States
Origin
Destination

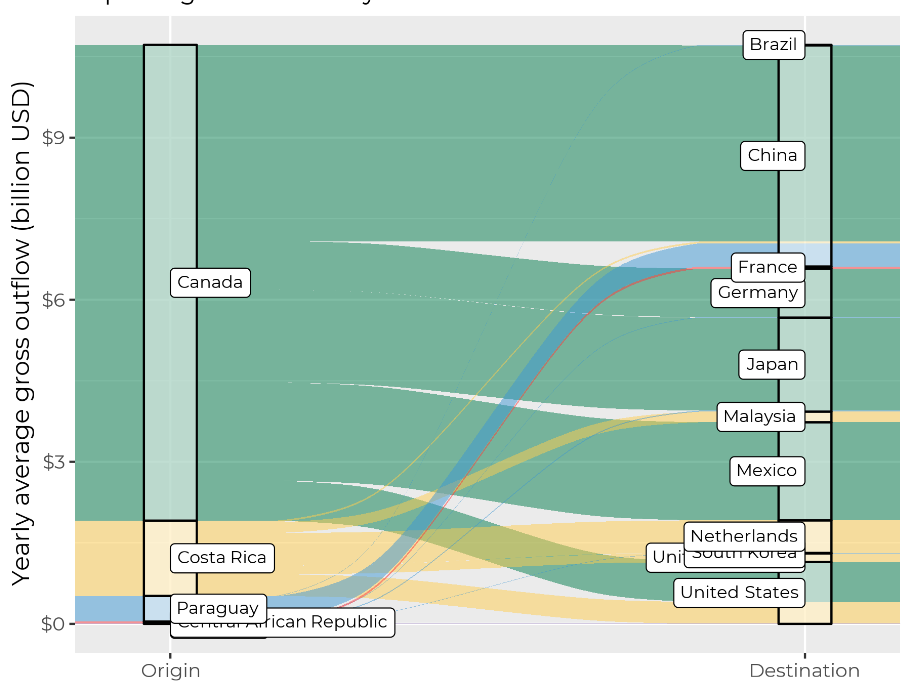
Pearls, precious stones and metals, jewelry, and coins

Top 5 origin countries by % of trade



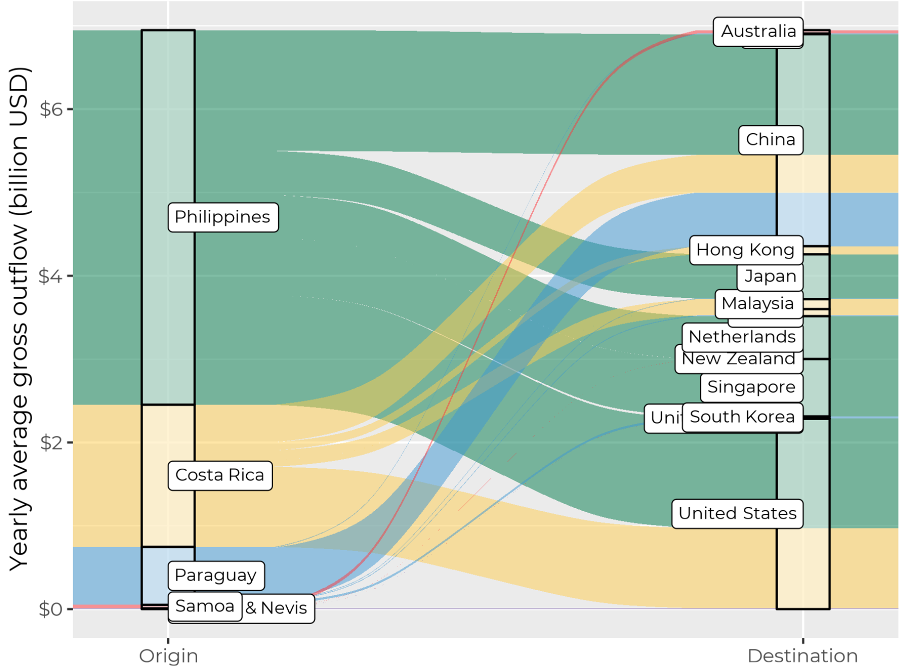
Nuclear reactors, boilers, and machinery

Top 5 origin countries by % of trade



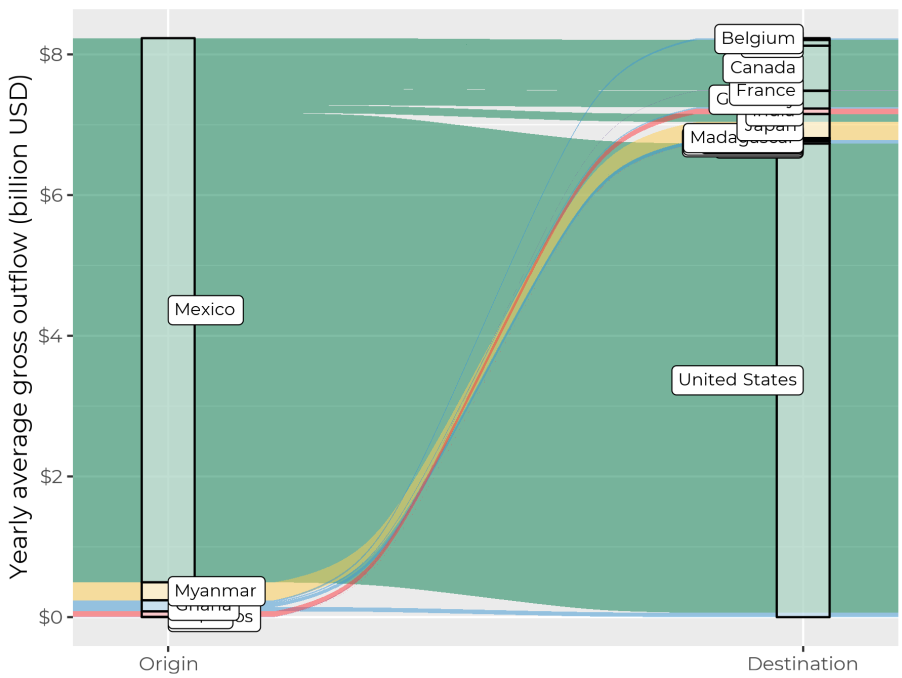
Electrical equipment, sound recorders, and televisions

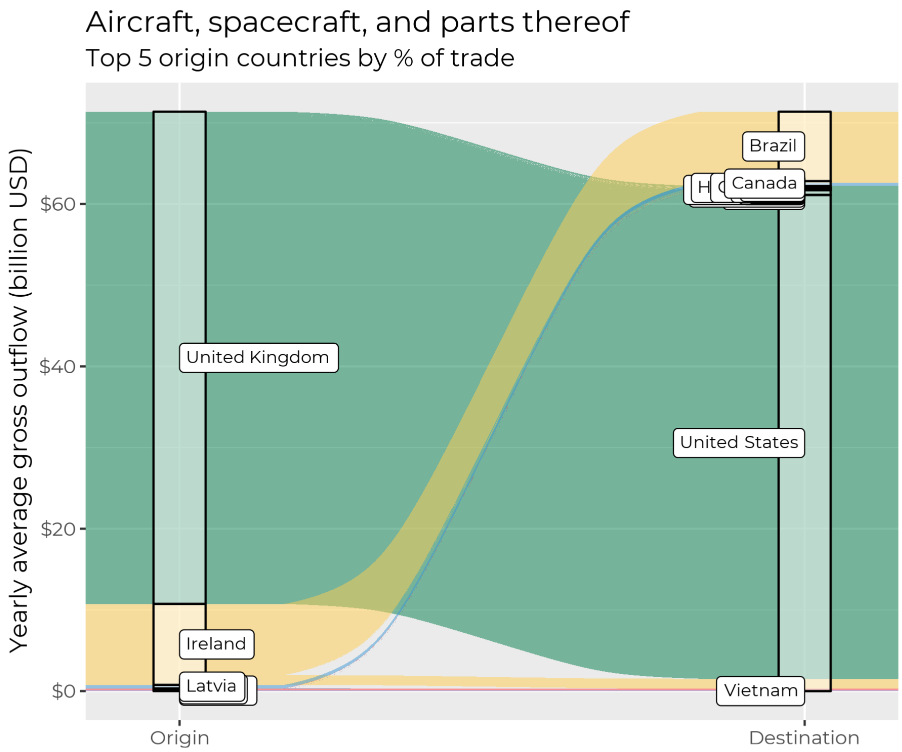
Top 5 origin countries by % of trade

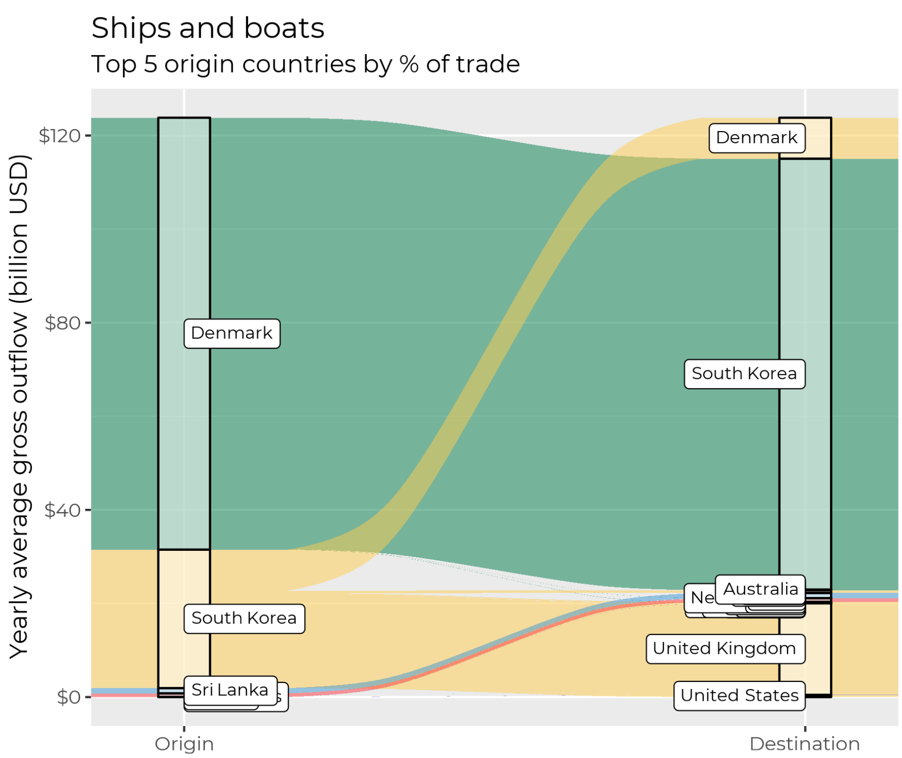


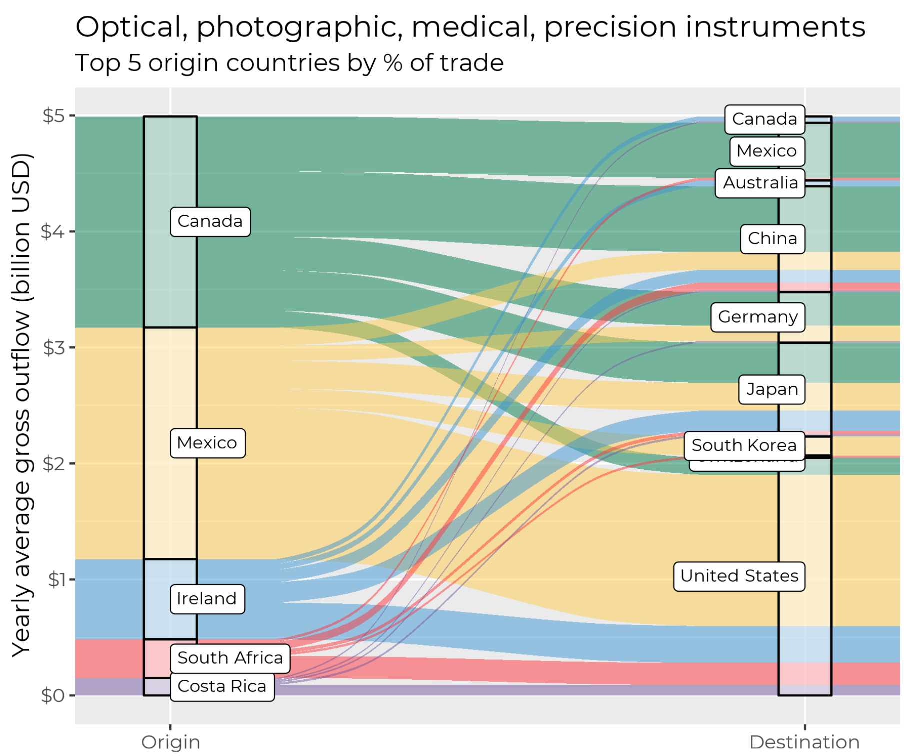
Vehicles other than railway or tramways

Top 5 origin countries by % of trade




Aircraft, spacecraft, and parts thereof
Top 5 origin countries by % of trade
Yearly average gross outflow (billion USD)
$60
$40
$20
$0
United Kingdom
Ireland
Latvia
Brazil
Canada
United States
Vietnam
Origin
Destination


Ships and boats
Top 5 origin countries by % of trade
Yearly average gross outflow (billion USD)
$120
$80
$40
$0
Denmark
South Korea
Sri Lanka
Denmark
South Korea
Australia
United Kingdom
United States
Origin
Destination



B Full country results

Country	ISO	Region	Income group	Million USD	% of GDP	% of trade
Afghanistan	AFG	Asia	LIC	$6	0.03%	0.07%
Albania	ALB	Europe	UMC	$174	1.71%	3.39%
Algeria	DZA	Africa	LMC	$4,225	3.25%	5.46%
Angola	AGO	Africa	LMC	$11,009	14.51%	16.27%
Antigua & Barbuda	ATG	Americas	HIC	$0	0.02%	0.04%
Argentina	ARG	Americas	UMC	$5,689	1.50%	5.24%
Armenia	ARM	Asia	UMC	$652	6.20%	11.71%
Aruba	ABW	Americas	HIC	$32	1.24%	2.37%
Australia	AUS	Oceania	HIC	$16,819	1.68%	5.01%
Austria	AUT	Europe	HIC	$5,104	1.39%	1.83%
Azerbaijan	AZE	Asia	UMC	$3,149	7.09%	15.54%

Country	ISO	Region	Income group	Million USD	% of GDP	% of trade
Bahamas	BHS	Americas	HIC	$147	1.44%	3.93%
Bahrain	BHR	Asia	HIC	$611	2.59%	2.30%
Bangladesh	BGD	Asia	LMC	$1,949	1.97%	5.15%
Barbados	BRB	Americas	HIC	$82	2.10%	4.67%
Belarus	BLR	Europe	UMC	$2,465	4.31%	3.86%
Belgium	BEL	Europe	HIC	$9,341	2.06%	1.22%
Belize	BLZ	Americas	UMC	$34	2.45%	3.13%
Benin	BEN	Africa	LMC	$53	0.70%	2.97%
Bermuda	BMU	Americas	HIC	$30	0.45%	2.99%
Bhutan	BTN	Asia	LMC	$14	1.22%	1.25%
Bolivia	BOL	Americas	LMC	$2,379	9.90%	15.24%
Bosnia & Herzegovina	BIH	Europe	UMC	$535	3.08%	3.51%
Botswana	BWA	Africa	UMC	$483	3.39%	4.00%
Brazil	BRA	Americas	UMC	$23,646	1.59%	7.98%
Brunei	BRN	Asia	HIC	$1,764	11.09%	13.54%
Bulgaria	BGR	Europe	UMC	$1,422	3.13%	3.25%
Burkina Faso	BFA	Africa	LIC	$81	0.70%	1.83%
Burundi	BDI	Africa	LIC	$8	0.39%	1.04%
Cambodia	KHM	Asia	LMC	$2,256	20.54%	22.54%
Cameroon	CMR	Africa	LMC	$380	1.67%	5.42%
Canada	CAN	Americas	HIC	$65,240	4.73%	8.38%
Cape Verde	CPV	Africa	LMC	$0	0.02%	0.03%
Central African Republic	CAF	Africa	LIC	$14	0.83%	4.52%
Chile	CHL	Americas	HIC	$5,161	2.90%	4.90%
China	CHN	Asia	UMC	$59,179	1.18%	2.49%
Colombia	COL	Americas	UMC	$3,829	1.55%	5.26%
Comoros	COM	Africa	LMC	$3	0.35%	2.05%
Congo	COG	Africa	LMC	$8,040	54.23%	54.65%

Country	ISO	Region	Income group	Million USD	% of GDP	% of trade
Costa Rica	CRI	Americas	UMC	$3,380	11.12%	15.96%
Côte d'Ivoire	CIV	Africa	LMC	$3,846	14.27%	20.13%
Croatia	HRV	Europe	HIC	$573	1.09%	1.79%
Cuba	CUB	Americas	UMC	$133	0.37%	1.83%
Cyprus	CYP	Asia	HIC	$150	0.69%	1.25%
Czech Republic	CZE	Europe	HIC	$5,172	2.71%	2.12%
Denmark	DNK	Europe	HIC	$12,314	3.70%	6.17%
Dominica	DMA	Americas	UMC	$4	0.87%	1.64%
Dominican Republic	DOM	Americas	UMC	$1,730	3.56%	9.02%
Ecuador	ECU	Americas	UMC	$2,556	3.85%	8.53%
Egypt	EGY	Africa	LMC	$6,756	3.73%	11.21%
El Salvador	SLV	Americas	LMC	$974	5.78%	8.26%
Estonia	EST	Europe	HIC	$626	3.22%	2.38%
Eswatini	SWZ	Africa	LMC	$1	0.03%	0.03%
Ethiopia	ETH	Africa	LIC	$683	1.94%	5.62%
Fiji	FJI	Oceania	UMC	$67	1.82%	2.18%
Finland	FIN	Europe	HIC	$3,884	1.64%	2.90%
France	FRA	Europe	HIC	$18,752	0.76%	1.77%
Gabon	GAB	Africa	UMC	$258	3.22%	5.65%
Gambia	GMB	Africa	LIC	$8	0.58%	1.64%
Georgia	GEO	Asia	UMC	$383	3.72%	6.98%
Germany	DEU	Europe	HIC	$33,306	1.00%	1.52%
Ghana	GHA	Africa	LMC	$2,342	8.29%	15.10%
Greece	GRC	Europe	HIC	$1,653	0.67%	2.00%
Grenada	GRD	Americas	UMC	$0	0.07%	0.13%
Grenadines	VCT	Americas	UMC	$4	0.64%	1.18%
Guatemala	GTM	Americas	UMC	$1,574	4.46%	9.10%
Guinea	GIN	Africa	LIC	$66	1.41%	2.62%

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Guinea-Bissau	GNB	Africa	LIC	$0	0.01%	0.07%
Guyana	GUY	Americas	UMC	$86	3.22%	3.54%
Honduras	HND	Americas	LMC	$614	4.65%	7.78%
Hong Kong	HKG	Asia	HIC	$35,582	15.44%	3.52%
Hungary	HUN	Europe	HIC	$2,680	2.10%	1.53%
Iceland	ISL	Europe	HIC	$690	4.00%	7.28%
India	IND	Asia	LMC	$13,544	0.96%	3.07%
Indonesia	IDN	Asia	UMC	$9,339	1.69%	3.91%
Iran	IRN	Asia	UMC	$4,166	1.36%	3.64%
Ireland	IRL	Europe	HIC	$10,842	4.73%	5.64%
Israel	ISR	Asia	HIC	$4,081	1.89%	3.77%
Italy	ITA	Europe	HIC	$3,259	0.17%	0.40%
Jamaica	JAM	Americas	UMC	$333	2.71%	4.96%
Japan	JPN	Asia	HIC	$20,064	0.40%	1.57%
Jordan	JOR	Asia	UMC	$554	2.39%	2.51%
Kazakhstan	KAZ	Asia	UMC	$8,778	5.44%	9.84%
Kenya	KEN	Africa	LMC	$507	1.89%	4.62%
Kuwait	KWT	Asia	HIC	$1,163	0.95%	1.26%
Kyrgyz Republic	KGZ	Asia	LMC	$418	7.22%	7.25%
Lao PDR	LAO	Asia	LMC	$1,118	7.55%	14.65%
Latvia	LVA	Europe	HIC	$557	1.98%	2.22%
Lebanon	LBN	Asia	UMC	$419	1.57%	3.23%
Lesotho	LSO	Africa	LMC	$0	0.01%	0.01%
Lithuania	LTU	Europe	HIC	$1,620	3.96%	3.26%
Macao	MAC	Asia	HIC	$320	2.08%	3.60%
Macedonia	MKD	Europe	UMC	$399	4.39%	4.47%
Madagascar	MDG	Africa	LIC	$308	3.72%	9.15%
Malawi	MWI	Africa	LIC	$50	0.90%	1.71%

Country	ISO	Region	Income group	Million USD	% of GDP	% of trade
Malaysia	MYS	Asia	UMC	$14,984	7.57%	4.86%
Maldives	MDV	Asia	UMC	$9	0.49%	0.83%
Mali	MLI	Africa	LIC	$210	2.33%	4.55%
Malta	MLT	Europe	HIC	$434	4.50%	4.28%
Mauritania	MRT	Africa	LMC	$47	0.80%	1.18%
Mauritius	MUS	Africa	HIC	$261	2.86%	4.07%
Mexico	MEX	Americas	UMC	$57,367	5.48%	9.72%
Moldova	MDA	Europe	LMC	$193	3.52%	3.44%
Mongolia	MNG	Asia	LMC	$454	7.66%	8.47%
Morocco	MAR	Africa	LMC	$2,411	2.84%	4.98%
Mozambique	MOZ	Africa	LIC	$635	5.42%	9.47%
Myanmar	MMR	Asia	LMC	$1,574	2.53%	7.13%
Namibia	NAM	Africa	UMC	$662	5.71%	5.00%
Nepal	NPL	Asia	LMC	$538	3.26%	8.64%
Netherlands	NLD	Europe	HIC	$10,133	1.30%	1.20%
New Zealand	NZL	Oceania	HIC	$2,619	1.94%	4.44%
Nicaragua	NIC	Americas	LMC	$1,276	10.42%	12.40%
Niger	NER	Africa	LIC	$58	0.78%	2.59%
Nigeria	NGA	Africa	LMC	$8,712	2.80%	8.98%
Norway	NOR	Europe	HIC	$10,729	2.80%	5.65%
Oman	OMN	Asia	HIC	$4,062	7.82%	7.85%
Pakistan	PAK	Asia	LMC	$2,440	1.25%	4.08%
Palau	PLW	Oceania	HIC	$1	0.42%	0.76%
Panama	PAN	Americas	HIC	$636	2.61%	3.52%
Papua New Guinea	PNG	Oceania	LMC	$276	7.58%	7.30%
Paraguay	PRY	Americas	UMC	$1,240	5.20%	9.10%
Peru	PER	Americas	UMC	$4,588	4.11%	9.92%
Philippines	PHL	Asia	LMC	$8,939	5.48%	8.47%

Country	ISO	Region	Income group	Million USD	% of GDP	% of trade
Poland	POL	Europe	HIC	$6,291	1.44%	2.07%
Portugal	PRT	Europe	HIC	$1,256	0.59%	1.03%
Qatar	QAT	Asia	HIC	$3,608	4.03%	5.45%
Russia	RUS	Europe	UMC	$41,694	3.00%	7.44%
Rwanda	RWA	Africa	LIC	$53	0.63%	1.89%
Samoa	WSM	Oceania	UMC	$16	2.15%	3.65%
São Tomé and Príncipe	STP	Africa	LMC	$0	0.13%	0.29%
Saudi Arabia	SAU	Asia	HIC	$3,678	0.79%	1.16%
Senegal	SEN	Africa	LMC	$263	1.68%	3.69%
Seychelles	SYC	Africa	HIC	$29	2.11%	1.51%
Singapore	SGP	Asia	HIC	$27,794	13.26%	4.85%
Slovak Republic	SVK	Europe	HIC	$3,127	3.47%	2.35%
Slovenia	SVN	Europe	HIC	$708	1.65%	1.51%
Solomon Islands	SLB	Oceania	LMC	$19	1.82%	2.59%
South Africa	ZAF	Africa	UMC	$23,565	8.30%	17.90%
South Korea	KOR	Asia	HIC	$13,473	1.20%	1.84%
Spain	ESP	Europe	HIC	$6,438	0.52%	1.19%
Sri Lanka	LKA	Asia	LMC	$1,108	2.76%	5.45%
St. Kitts & Nevis	KNA	Americas	HIC	$17	2.55%	5.85%
St. Lucia	LCA	Americas	UMC	$22	1.63%	3.24%
Sudan	SDN	Africa	LIC	$444	1.06%	2.99%
Suriname	SUR	Americas	UMC	$59	1.60%	1.82%
Sweden	SWE	Europe	HIC	$3,932	0.84%	1.41%
Switzerland	CHE	Europe	HIC	$28,904	4.87%	6.36%
Syria	SYR	Asia	LIC	$990	1.00%	3.75%
Tanzania	TZA	Africa	LMC	$6,700	17.24%	40.51%
Thailand	THA	Asia	UMC	$11,964	4.13%	3.70%
Togo	TGO	Africa	LIC	$78	2.36%	4.44%

Country	ISO	Region	Income group	Million USD	% of GDP	% of trade
Tonga	TON	Oceania	UMC	$1	0.15%	0.31%
Trinidad & Tobago	TTO	Americas	HIC	$4,277	18.59%	19.51%
Tunisia	TUN	Africa	LMC	$1,354	3.43%	4.20%
Turkey	TUR	Asia	UMC	$6,898	1.12%	2.83%
Uganda	UGA	Africa	LIC	$126	0.77%	2.45%
Ukraine	UKR	Europe	LMC	$11,316	8.74%	10.64%
United Arab Emirates	ARE	Asia	HIC	$20,708	5.90%	3.50%
United Kingdom	GBR	Europe	HIC	$45,373	1.90%	4.73%
United States	USA	Americas	HIC	$220,848	1.49%	6.92%
Uruguay	URY	Americas	HIC	$955	2.56%	6.86%
Vanuatu	VUT	Oceania	LMC	$1	0.10%	0.22%
Venezuela	VEN	Americas	UMC	$4,610	2.84%	6.80%
Vietnam	VNM	Asia	LMC	$9,053	7.69%	5.61%
Yemen	YEM	Asia	LIC	$8,623	36.55%	57.51%
Zambia	ZMB	Africa	LMC	$497	2.66%	4.28%
Zimbabwe	ZWE	Africa	LMC	$694	5.44%	8.06%

Table 4: Average gross annual outflows during 2000-2018.