Misreported Trade*

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Abstract

We propose a methodology to measure misreported trade across countries and over time in a consistent and comparable manner. Our methodology does not require *a priori* assumptions about which countries may be more or less likely to misreport. We derive seven indices on overall misreporting, as well as over- and under-reporting of trade, exports, and imports. Exploring bilateral trade data from 1996-2015, we derive country rankings and discuss prominent cases, such as China. We conclude with an application, documenting positive and statistically meaningful correlations of tariff and VAT rates with our import under-reporting index, even after controlling for potentially confounding factors.

JEL Classifications: F13, F14, H26
Keywords: international trade, trade misreporting, tariff rates, VAT rates

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1 Introduction

In 1996, the US recorded a $39.5 billion trade deficit with China (Feenstra et al., 1999). However, China reported that value to be $10.5 billion. These official trade figures, reported by the world's two largest economies, differ by $29 billion – a value that is equivalent to the collective GDP of Uruguay and Zimbabwe at that time. Which number is correct or, more realistically, to what degree are both incorrect? Previous research has produced evidence suggesting (i) an under-reporting of Chinese exports to avoid value-added taxes (VAT), as well as (ii) tariff evasion at the US border through under-reporting of imports (e.g., see Ferrantino et al., 2012). In fact, if the latter were true, this $29 billion gap may be even *higher*. This simple but prominent example illustrates that discrepancies in reported trade statistics are unlikely to be explainable by the development status of reporting countries alone. For example, comparable gaps in reported trade numbers have been identified between Canada and the US, two of the richest OECD countries (Feenstra et al., 1999). Thus, it is not sufficient to simply assume the US numbers to be correct and the Chinese numbers to be incorrect.

But why would such discrepancies in reported trade data matter? In reality, fabricated trade statistics can put policymakers in difficult situations since trade data play a central role in macroeconomic, trade, and foreign policy considerations. One may only think about public policies related to protectionist tariff measures, trade negotiations, capital controls, or export support programs.[1] Trade data might also substantially influence countries' internal democratic decision-making processes. For

[1]For example, Feenstra et al. (1999) describe how bilateral trade deficits act as one of the principal drivers in the US trade disputes with East Asia. UNCTAD (2016) find the extensive use of export under-reporting as one of the main tools of capital flight from four resource-rich developing countries (Côte d'Ivoire, Nigeria, South Africa, and Zambia). Kar and Spanjers (2015) suggest that around $1 trillion in illicit capital outflows left emerging countries in 2013, and over 83 per cent of that number is suggested to be transported through trade misinvoicing. Finally, Jara and Escaith (2012) give a detailed account of how important international trade statistics are for national and international economic policymaking.

instance, the magnitude of the US trade deficit with China played a substantial role in the 2016 presidential elections (Schneider-Petsinger, 2017). Similarly, trade relationships with China played a crucial role in the Brexit referendum (Colantone and Stanig, 2018). Perhaps most importantly from a fiscal perspective, misreporting trade data can directly decrease public resources, for example via lost revenue from tariff evasion or the misuse of export support programs. Further, any evidence-based policymaking or empirical analysis using misreported trade data might indicate misleading outcomes of targeted policy interventions.[2] Similarly, *international trade costs* or the *costs of trade* (for example, the costs of cheap Chinese imports on employment) might be erroneously estimated if trade data are systematically misreported.[3]

Overall, we can summarize this discussion with three key points: (i) trade data are important for policymaking, (ii) misreporting trade data exists and is unlikely exclusive of rich countries, and, as a consequence of the latter point, (iii) it is insufficient to use one country's data as the automatic benchmark for correct reporting of any bilateral trade estimate. To date, several studies exist that analyse and quantify underlying incentives for misreporting. For example, Fisman and Wei (2004), Javorcik and Narciso (2008), Mishra et al. (2008), and Ferrantino et al. (2012) estimate the impact of tariffs on under-reporting imports; Ferrantino et al. (2012) investigate under-reporting of exports to avoid tax payments. However, these studies usually have to rely on the assumption that countries commonly labelled as developed report their bilateral trade data correctly, whereas developing countries do not. Addition-

[2]For example, Egger and Larch (2012) find that disregarding tariff evasion suggests unrealistically higher welfare effects of a full liberalisation of import tariffs.

[3]For example, The World Bank and the United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP) jointly publish a global dataset of bilateral trade costs (available at `https://data.worldbank.org/data-catalog/trade-costs-dataset`). To measure bilateral trade costs, they simply ignore the issue of misreporting, which might significantly alter the estimated trade costs. Autor et al. (2013) find that a cheap Chinese import surge resulted in higher unemployment and low wage rates in the US manufacturing sectors, which is estimated using the UN Comtrade database that disregards any possibility of misreporting.

ally, the vast majority of the associated studies focus on individual country pairs or a small group of selected trading partners to investigate trade misreporting, whereas a misreporting index that is comparable across countries and over time has remained elusive.[4]

In the following pages, we aim to provide just that: To objectively derive a trade misreporting index that is (i) non-discriminatory (i.e., without an *a priori* definition of one country's reports as more credible than another's), (ii) scale-independent (i.e., independent of country, economy, and population size), and (iii) comparable across countries and over years. We want to briefly sketch our methodology that constitutes the main contribution of this paper. First, we identify a country's numerical reporting distance of each reported bilateral trade flow to its respective counterpart's reported value. Second, we aggregate that country's reporting discrepancies with (i) all trading partners (ii) for all goods (iii) in a given year to derive a country- and year-specific *weighting factor*. Intuitively, that weighting factor proxies "how much we can believe that country's trade numbers in that year, according to all their trade partners' reports". Third, these weighting factors allow us to calculate a weighted trade value for individual trade entry. Thus, the resulting estimates of each bilateral trade flow are solely determined by available data and remain free from any *a priori* assumptions about who may or may not be reporting accurately. Fourth and final, we put the estimated trade flows in relation to the actual trade flows to derive a general trade misreporting index ranging from zero to one.[5] We then repeat these steps to

[4]A few studies attempt to 'clean' trade data (e.g., see Gehlhar, 1996) but usually have to make *ad-hoc* decisions about which trade partner is 'reliable'. Gaulier and Zignago (2010) estimate cost, insurance and freight (CIF) rates using a gravity-type equation and then calculate country reliability as a function of reporting distance. Carrere and Grigoriou (2015) consider 'orphan' trade flows as cases where one partner reports a positive trade value, whereas its counterpart record zero trade.

[5]Specifically, we employ a variation of a Contest Success Function (CSF, e.g., see Buchanan et al., 1980) to measure $Index = \frac{estimated\ misreported\ trade}{estimated\ misreported\ trade + actual\ reported\ trade}$, where $0 \leq Index \leq 1$.

derive six specific over- and under-reporting indices for exports and imports – each of which is designed to analyse particular types of misreporting.

Applying this methodology, we then access bilateral trade data for up to 160 World Trade Organization (*WTO*) member countries from 1996-2015, incorporating over 58 million pairs of trade observations at the HS 4-digit level. For 2015, we find Togo to be the largest overall misreporter, followed by Antigua and Barbuda, Panama, and Afghanistan, whereas Canada emerges as the least misreporting country. In general, high-income OECD countries misreport the least, whereas low-income countries misreport relatively more over the entire sample period. However, and perhaps somewhat surprisingly, high-income non-OECD countries are the second highest export-misreporting country group, including Kuwait, Saudi Arabia, and the United Arab Emirates. These nations rely heavily on exporting oil and other natural resources, which could explain their large degree of misreporting as a tool of illicit cross-border capital movement. These findings are also commensurate with the regional average, placing the Middle East and North Africa as the top export misreporting region. Finally, North America remains the least misreporting region, both concerning exports and imports, while Sub-Saharan Africa emerges as the largest import misreporting region. Our findings are consistent when (i) employing alternative conversions from cost-insurance-and-freight (CIF) values to free-on-board (FOB) terms, (ii) addressing the role of entrepôt trade, and (iii) constraining our analysis to a more homogeneous group of countries with high-income OECD nations only.

As one particular case study of our indices, we then turn to China. We find that China's average export misreporting index to be around 40 per cent higher than that of OECD countries. However, that is not consistent across all types of misreporting: China's average *import* misreporting is comparable to the OECD average throughout the 1996-2015 period. Further, China's imports are dominated by over-reporting, while Chinese exports appear largely under-reported. Interestingly, however, these trends are reversed in recent years. Chinese overall trade misreporting started to decline significantly right before 2001 – the year when the country joined the WTO. Quite possibly, this could reflect the transparency and gradual liberalisation requirements the country had to comply with for its accession into the multilateral trading system. Furthermore, our indices suggest that possible illicit capital outflows through import over-reporting and export under-reporting declined over the years, corresponding to China's gradual relaxation of its capital outflow control regimes. However, possible inflows of 'hot money' through export over-reporting may have increased in recent years.

To conclude the paper, we present an empirical application of one of our derived indices as an example application in practice. Specifically, we explore import under-reporting – the type of trade misreporting that has received the most attention in the literature to date. Intuitively, as indicated by various country-specific studies, importers may intentionally under-report to evade tariffs (e.g., see Fisman and Wei, 2004, Mishra et al., 2008, Ferrantino et al., 2012). Indeed, we find evidence consistent with this hypothesis as applied tariff rates remain a positive and statistically powerful predictor of our import under-reporting index throughout a series of regressions, using panel data for our sample countries from 1996-2015. This result prevails even when we control for the country- and year-fixed effects, in addition to potentially confounding variables, such as trade openness, democracy, or corruption levels. Finally, we also find VAT rates to be positively associated with import under-reporting. In addition to the explicit implications of these results, we hope this application provides an example for the usefulness of our indices in analysing a range of research questions related to misreported trade data in a panel dimension across many countries and years.

Overall, we aim to contribute to the research community in two ways. First, to the best of our knowledge, we present the first method to measure country- and time-specific misreporting of trade data which is free from *a priori* ad-hoc assumptions about who does and does not report correctly. In practice, this method could be applied to any level of disaggregated trade data. Second, we provide a ready-to-use set of trade misreporting indices, which are comparable across countries and over time. Specifically, we derive seven distinct indices that explore (*i*) overall trade misreporting, (*ii*) export misreporting, (*iii*) import misreporting, (*iv*) export over-reporting, (*v*) export under-reporting, (*vi*) import over-reporting, and (*vii*) import under-reporting. Depending on the research question, we hope that these indices can help us to understand better both the determinants and the consequences of various types of trade misreporting on a global level.

The paper proceeds with a short background discussion of existing studies on trade misreporting. Section 3 introduces our theoretical framework, whereas Section 4 takes the developed indices to the data and presents initial findings, including a case study on China. Section 5 presents one empirical application and Section 6 offers concluding remarks.

2 Background

2.1 Why Misreport?

In theory, international mirror trade data should be comparable, since each transaction is reported twice by the trading partners to the corresponding public authorities of their countries. However, similar to other publicly recorded economic activities where deviations from actual figures can generate rents, discrepancies in reported trade data have become a historical phenomenon, and their existence widely recognised in the economics literature.[6] These discrepancies in reported bilateral trade statistics, which Ferrantino et al. (2012) describe as "endemic globally", continue to stifle economic research and policymaking. Exporting and importing parties may have several incentives for misreporting trade data. For example, tariffs or other protectionist trade policies can encourage importers to under-report; capital controls may lead to misreporting in order to channel capital into or out of the country; export support programs might inspire exporters to inflate export earnings. We refer to Bhagwati (1964, 1967, 1981) for details on different types of trade misreporting, their underlying motivations and economic implications, as well as possible ways of faking trade invoices in practice.

2.2 Measurement of Misreported Trade Data

While these motivations of misreporting trade are much better understood in theory, measurement methods used to assess misreporting have received relatively little attention. The few existing studies concerned with measuring discrepancies in trade data can broadly be divided into two groups. Early works simply measure differences of reported mirror trade flows by bilateral trading partners as misreporting (for example, see Morgenstern et al., 1963, Bhagwati, 1964, and Sheikh, 1974, among others). More recently, Fisman and Wei (2004) introduce the use of the difference in logarithms of bilateral mirror trade flows to study misreporting. Initially, they calculate reporting discrepancies as $gap\ value = log(export\ value) - log(import\ value)$. However, because of its logarithmic definition, this specification ignores transactions where one partner

[6] For example, 19^{th} century Italian economist Galileo Ferraris (1885) measured the movement of gold from France to Great Britain, finding that only a varying part of the total exports and imports of any country was recorded in the official statistics. Morgenstern et al. (1963) and Bhagwati (1964) provide an early account of trade misreporting.

recorded some trade, but the corresponding partner reported nothing. To take into consideration these extreme cases of so-called "complete smuggling", Mishra et al. (2008) and Fisman and Wei (2009) use a second measure, where the reporting gap is measured as $evasion = log(1 + imports) - log(1 + exports)$. A number of studies thereafter discussing trade misreporting use similar specifications to measure discrepancies in reported trade data (for example, see Javorcik and Narciso, 2008, 2017, Ferrantino et al., 2012, and Mishra et al., 2008, among others).

These methods merely capture the trade *reporting* gap. This gap can be attributed to misreporting by a specific country only when one assumes that the partner country's reported trade data is correctly recorded. For example, Javorcik and Narciso (2008) consider Germany's reported trade data as accurate when exploring the misreporting of its ten Eastern European trading partners; Mishra et al. (2008) regard the trade data reported by India's top 40 trading partners as correct; Ferrantino et al. (2012) analyse US imports from China and consider the US data as accurate. In turn, Ferrantino et al. (2012) propose the possibility of import under-reporting by the US only when the Chinese data are assumed fixed. In sum, all these studies have to make an ad-hoc assumption that one side of each trading relationship reports correctly, whereas the other does not.

Perhaps as a consequence of lacking a comparable and consistent trade misreporting index, the literature usually focuses on one trading partner (e.g., Fisman and Wei, 2004, and Ferrantino et al., 2012) or the few major trade partners of one country (e.g., see Mishra et al., 2008, or Javorcik and Narciso, 2008). Some studies consider a select group of countries, such as Javorcik and Narciso (2017) who analyse bilateral exports from Germany, the US, and France, as well as imports by 15 countries that joined the *WTO* between 1996 and 2008.[7]

[7] Kellenberg and Levinson (2016) make an attempt to examine misreporting using a larger panel

2.3 Types of Misreporting

Moreover, the prevailing literature rarely attempts to capture the extent of all four types of trade misreporting by a particular reporting country with over- and under-reporting of exports and imports. For example, Fisman and Wei (2004), Javorcik and Narciso (2008), Mishra et al. (2008), Ferrantino et al. (2012), and Javorcik and Narciso (2017) try to capture and explain import under-reporting; Ferrantino et al. (2012) also explore export under-reporting (also see Arslan and van Wijnbergen, 1993). As one of the few exceptions, Buehn and Eichler (2011) aim to capture all types of trade misreporting, but employ aggregate trade data between the US and 86 countries. Again, Buehn and Eichler (2011) start from the premise that one country (in this case the US) reports trade data accurately.

Overall, we lack a consistent empirical method that is comparable across countries and over time to estimate trade misreporting without making *a priori* assumptions about who does and does not report correctly.

3 Theoretical Framework

Following the existing literature, the dual nature of reported trade data provides us with a straightforward way to identify the existence of misreporting. Nevertheless, assigning any discrepancies to one of the trading partners is challenging since differences may be induced by either or both parties involved. As an example, consider the export of coffee (HS 4-digit code 0901) from Brazil to Tunisia. Let us assume that, in a given year, Brazil reports exporting $100,000 worth of coffee to Tunisia; however,

including trade data between 126 countries over 11 years. However, they use aggregated trade data which may not be able to capture the extent of trade misreporting correctly – an aspect we consider in our data section.

Tunisia reports only $60,000 worth of coffee imports from Brazil. Who is misreporting? We will use this example throughout this section to illustrate the derivation of our index. To keep it simple, we assume that both values are in so-called free-on-board (FOB) values.[8] To facilitate readability, we omit time subscripts t throughout this section as all calculations are of a static nature, i.e., take place in the same year.

3.1 Step 1: Deriving Weighted Trade Values

Our first step to derive a comparable index of trade misreporting consists in identifying the degree to which a given country misreports its exports and imports in a given year. Then, we use these numbers to calculate the weighted value for each bilateral trade transaction. Thus, we begin by considering the 'reporting distance' of all bilateral trade relationships reported by a country and all of its trading partners.

3.1.1 Export Weighting Factors (*EWF*s)

Beginning with exports, consider the top panel of Table 1, displaying the hypothetical relationships between exporting Brazil and importing Tunisia. We can observe three types of trade links: Exports that are reported by Brazil but unreported (as imports) by Tunisia; exports reported by both countries, indicated by the shaded grey areas; and imports reported by Tunisia that are not reported as exports from Brazil. We can then extend this picture to *all* countries that Brazil is linked to in terms of exports. To keep things simple in this example, Table 1 assumes Brazil's exports are linked to no more than three countries overall in a given year: Tunisia, Bangladesh, and Australia.

[8] Following the Department of Economic and Social Affairs of the United Nations (2010) recommendation, countries use the FOB valuation for exports (at the border of the exporting county) and the cost, insurance, and freight (CIF-type) valuation for imports (at the border of the importing country) while reporting their trade values. We will return to this difference in our empirical section (these definitions do not affect our derived indices in meaningful ways).

(Note that this includes countries that report having imported something from Brazil but Brazil does not record any of those exports.)

Table 1: Hypothetical mirror trade flow data reported by exporter Brazil (s_1) and *all* its destination countries: Tunisia (d_1), Bangladesh (d_2), and Australia (d_3).

	HS-4 code	Source	Destination	Export value ($000)	Import value ($000)	Absolute Reporting distance ($000)
$(s_1 \rightleftharpoons d_1)$	0110	Brazil (s_1)	Tunisia (d_1)	15		15
	0806	Brazil (s_1)	Tunisia (d_1)	20		20
	0901	Brazil (s_1)	Tunisia (d_1)	100	60	40
	4040	Brazil (s_1)	Tunisia (d_1)	40	50	10
	5050	Brazil (s_1)	Tunisia (d_1)	50	40	10
	6060	Brazil (s_1)	Tunisia (d_1)		25	25
	7009	Brazil (s_1)	Tunisia (d_1)		10	10
	8080	Brazil (s_1)	Tunisia (d_1)		5	5
	8(3)	5(3)	6(3)	225(190)	190(150)	135
$(s_1 \rightleftharpoons d_2)$	1010	Brazil (s_1)	Bangladesh (d_2)	30		30
	2020	Brazil (s_1)	Bangladesh (d_2)	85	70	15
	3030	Brazil (s_1)	Bangladesh (d_2)	60	50	10
	4040	Brazil (s_1)	Bangladesh (d_2)	80	100	20
	5050	Brazil (s_1)	Bangladesh (d_2)	100	150	50
	6060	Brazil (s_1)	Bangladesh (d_2)		80	80
	7009	Brazil (s_1)	Bangladesh (d_2)		40	40
	8080	Brazil (s_1)	Bangladesh (d_2)		20	20
	8(4)	5(4)	7(4)	355(325)	510(370)	265
$(s_1 \rightleftharpoons d_3)$	1010	Brazil (s_1)	Australia (d_3)	20		20
	2020	Brazil (s_1)	Australia (d_3)	100	125	25
	3030	Brazil (s_1)	Australia (d_3)	120	140	20
	4040	Brazil (s_1)	Australia (d_3)	240	200	40
	5050	Brazil (s_1)	Australia (d_3)		15	125
	5(2)	4(2)	3(2)	480(460)	480(465)	120
$(s_1 \rightleftharpoons d_n, n = 3)$	21(10)	14(10)	16(10)	1,060(975)	1,180(985)	520

Notes: Both exports and imports are considered here in comparable *FOB* values to eliminate discrepancies resulting from *FOB* and *CIF* price reports by the exporter and the importers, respectively.

Our first step consists in using the absolute reporting distance of Brazil's reported export values with the respective importer-reported import values. We consider the unreported trade values as zero trade where one party reports non-zero trade, whereas the corresponding partner reports nothing. In the example of Table

1, Brazil's reported exports total \$1,060,000, whereas its partners report importing a total of \$1,180,000 from Brazil in aggregate. However, the total absolute reporting distance between Brazilian and their counterparts' numbers becomes \$520,000. We then derive the *export weighting factor* (*EWF*) for Brazil in this example as one minus the ratio of the total absolute reporting distance divided by the sum of Brazil's reported exports and its partners' reported imports. In this case, we derive a value of $1 - \frac{520{,}000}{1{,}060{,}000+1{,}180{,}000} = 0.768$. Intuitively, the closer the *EWF* comes to zero, the more misreporting we detect; as the *EWF* approaches one, less misreporting is detected.

From this example, we can formalize the derivation of the *EWF*. Considering total reported exports x of all products K (with $k \in [1, ..., K]$) from all source countries S (with $s \in [1, ..., S]$) to all destination countries D (with $d \in [1, ..., D]$), we can write

$$X_{sD}^{K} = \sum_{k=1}^{K} \sum_{d=1}^{D} x_{sd}^{k}. \tag{1}$$

In our simple example from Table 1, this corresponds to the reported exports of \$1,060,000. Further, the total reported imports (m) of all K products by all importing (destination) countries D from each source country s are calculated as

$$M_{Ds}^{K} = \sum_{k=1}^{K} \sum_{d=1}^{D} m_{ds}^{k}, \tag{2}$$

which corresponds to the reported imports of \$1,180,000 in Table 1. From here, we calculate the reporting distance (δ_{sd}^{k}) of each product as the difference of each reported export value (x_{sd}^{k}) from its mirror import value (m_{ds}^{k}) reported by the corresponding import partner as

$$\delta_{sd}^{k} = m_{ds}^{k} - x_{sd}^{k}. \tag{3}$$

Now we calculate the total absolute reporting distance (δ_{sD}^{K}) of all Brazil's reported export values from its counterparts' reported import values as

$$\delta_{sD}^{K} = \sum_{k=1}^{K} \sum_{d=1}^{D} |\delta_{sd}^{k}|. \tag{4}$$

In Table 1, this corresponds to \$520,000. Finally, the *EWF* for Brazil is then derived as one minus the ratio between the total absolute reporting distance and the sum of Brazil's reported total exports and all importing countries' reported total imports from Brazil as:

$$(EWF)_s^x = 1 - \frac{\delta_{sD}^{K}}{X_{sD}^{K} + M_{Ds}^{K}}. \tag{5}$$

Intuitively, if a country reports export values that are close to the reported import values by the respective importer, the country will score a high *EWF*; on the other hand, countries having higher discrepancies with their counterparts' reported imports will score a lower value. Naturally, the *EWF* ranges between zero and one.

3.1.2 Import Weighting Factors (*IWF*s)

If we consider trade from the importing country's perspective, we can derive an analogous weighting factor for imports. An example is provided in Table A1 in the appendix, where we consider Tunisia's imports, assuming three respective source countries: Brazil, Bangladesh, and Australia. We now consider the total value of Tunisia's reported imports from all its import partners and all its import sources' reported export values to Tunisia. We then calculate the total absolute reporting distance of Tunisia's reported imports from its counterparts' reported exports. Finally, we derive the *import weighting factor* (*IWF*). Formally, the *IWF* is derived analogously to equation 5 with

$$(IWF)_d^m = 1 - \frac{\delta_{dS}^{K}}{M_{dS}^{K} + X_{Sd}^{K}}, \tag{6}$$

where $\delta^K_{dS} = \sum_{k=1}^{K} \sum_{s=1}^{S} |\delta^k_{ds}|$, $M^K_{dS} = \sum_{k=1}^{K} \sum_{s=1}^{S} m^k_{ds}$, and $X^K_{Sd} = \sum_{k=1}^{K} \sum_{s=1}^{S} x^k_{sd}$. These three terms constitute the counterparts of equations 4, 1, and 2 from the export perspective.

3.1.3 Calculating Weighted Trade Values

The *EWF* and *IWF* values provide proxies for the reliability levels with which each country reports its exports and imports, based entirely on reported data, as opposed to ad-hoc assumptions about the reliability of one country's data over another. With this information, we can now revisit each trade entry – for instance, our example coffee exports from Brazil to Tunisia. If Brazil reports an exported value of \$100,000, but Tunisia reports importing \$60,000, then which entry is more reliable and by how much? We can now use the *EWF* and the *IWF* values to weigh these values according to how reliable the respective country's reporting is in the given year. Formally, we calculate the weighted export value of product k (e.g., coffee) from source country s (e.g., Brazil) to destination country d (e.g., Tunisia) as

$$\hat{x}^k_{sd} = \frac{(EWF)^x_s}{(EWF)^x_s + (IWF)^m_d} \times x^k_{sd} + \frac{(IWF)^m_d}{(EWF)^x_s + (IWF)^m_d} \times m^k_{ds}. \tag{7}$$

Intuitively, if Brazil had a strong *EWF* and Tunisia had a weak *IWF*, then the first fraction ($\frac{(EWF)^x_s}{(EWF)^x_s + (IWF)^m_d}$) would be closer to one. Consequently, the value reported by Brazil would carry more weight, i.e., the predicted actual export value ($\hat{x}^k_{sd}$) would be closer to \$100,000. Alternatively, if Tunisia's *IWF* was more credible, $\hat{x}^k_{sd}$ would converge closer to \$60,000. In our example, the predicted export of coffee from Brazil to Tunisia becomes $(\frac{0.768}{0.768+0.679} \times 100,000 + \frac{0.679}{0.768+0.679} \times 60,000) = \$81,230$ (see Table A1 for Tunisia's *IWF* in this example). This method allows us to derive a *weighted* value for every *reported* trade entry, including situations where one country reports no exports but its corresponding import partner does report a non-zero value.[9]

Likewise, we can derive predicted import values ($\widehat{m}^k_{ds}$) for each reported import product, using the importing country's *IWF* and the corresponding export country's *EWF*. Formally, this translates to

$$\widehat{m}^k_{ds} = \frac{(IWF)^m_d}{(IWF)^m_d + (EWF)^x_s} \times m^k_{ds} + \frac{(EWF)^x_s}{(IWF)^m_d + (EWF)^x_s} \times x^k_{sd}. \tag{8}$$

In sum, equations 7 and 8 provide us with a weighted value for every import and export entry in the product-country-year dimension.

3.2 Step 2: Constructing Trade Misreporting Indices

With these derivations, we are now ready to construct misreporting indices. Specifically, for every country and year, we can derive (i) an overall misreporting index, (ii) an under-reporting index, and (iii) an over-reporting index for exports and imports. We begin with considering exports and then move to imports in Section 3.2.2 before considering overall misreporting in Section 3.2.3.

3.2.1 Export Misreporting Indices (*EMI*s)

First, we find the misreported export value ($\tilde{x}^k_{sd}$) for each product as the difference between the reported value (x^k_{sd}) and the weighted value ($\widehat{x}^k_{sd}$):

$$\tilde{x}^k_{sd} = x^k_{sd} - \widehat{x}^k_{sd}. \tag{9}$$

[9]To illustrate this, consider our example from Table 1, where Tunisia reports $10,000 worth of glass mirror imports (HS 4-digit code 7009) from Brazil. Brazil, on the other hand, reports no export of this item to Tunisia. Using equation 7, we can estimate a weighted export value of glass mirrors from Brazil to Tunisia, which in this case becomes $(\frac{0.768}{0.768+0.679} \times 0 + \frac{0.679}{0.768+0.679} \times 10,000) = \$4,692$.

To gain an overall picture of a country's export misreporting, we need to sum up their product-wise misreported export values. However, exporters of a country might under-report some values but over-report others, based on the individual incentives. Therefore, a simple summation of product-wise misreported values would cancel out some of the negative and positive misreported values and, hence, we would fail to capture the actual magnitude of trade misreporting in that country and year.

To circumvent this issue, we sum the absolute values. Formally, we calculate the total absolute misreported export value $\tilde{X}_s^K$ for each source country s and all its export products k to all its export destinations d as

$$\tilde{X}_s^K = \sum_{k=1}^{K} \sum_{d=1}^{D} |\tilde{x}_{sd}^k|. \tag{10}$$

$\tilde{X}_s^K$ gives us a dollar estimate of the total absolute export misreporting of any given country in any given year. However, this would still make a comparison across countries and time difficult, since clearly countries that trade more and in larger volumes would report higher values of $\tilde{X}_s^K$. To derive a comparable index that is naturally bounded between zero and one, our final step consists in putting $\tilde{X}_s^K$ in perspective to the sum of the country's total reported export values (X_s^K) and the total absolute export misreporting value ($\tilde{X}_s^K$). This step is perhaps best comparable to a Contest Success Function (*CSF*, e.g., see Buchanan et al., 1980). Formally, we label the *overall* export misreporting index for source country s as EMI_s^x with

$$EMI_s^x = \frac{\tilde{X}_s^K}{\tilde{X}_s^K + X_s^K}. \tag{11}$$

Further, if we are specifically interested in export *under*-reporting, we can sum up the under-reported export values only. Thus, we consider only those $\tilde{x}_{sd}^k$ values from equation 9 that are negative. Denoting these with $\underline{x}_{sd}^{k}$, we arrive at the total under-reported export value of

$$\underline{X}_s^K = \sum_{k=1}^{K} \sum_{d=1}^{D} |\underline{x}_{sd}^k| \tag{12}$$

and the export under-reporting index becomes

$$EUI_s^x = \frac{\underline{X}_s^K}{\underline{X}_s^K + X_s^K}. \tag{13}$$

Similarly, assume we are interested in *over*-reported exports only, labeling these $\overline{x}_{sd}^{k}$. In this case, we only consider those values from equation 9 that return positive values, i.e., the reported export value is higher than the weighted value. Consequently, we derive the total over-reported export value via

$$\overline{X}_s^K = \sum_{k=1}^{K} \sum_{d=1}^{D} |\overline{x}_{sd}^k| \tag{14}$$

and the export over-reporting index becomes

$$EOI_s^x = \frac{\overline{X}_s^K}{\overline{X}_s^K + X_s^K}. \tag{15}$$

In sum, we can derive three distinct export misreporting indices: (i) the overall export misreporting index (EMI_s^x), (ii) the export under-reporting index (EUI_s^x), and (iii) the export over-reporting index (EOI_s^x).

3.2.2 Import Misreporting Indices (*IMI*s)

The corresponding indices for import misreporting follow analogously and we only sketch them briefly here. Specifically, if we are interested in the *overall* degree of import misreporting, we first calculate misreported import values ($\tilde{m}_{ds}^k$) for each product as the difference between the reported value (m_{ds}^k) and the weighted value ($\widehat{m}_{ds}^k$) as

$$\tilde{m}_{ds}^k = m_{ds}^k - \widehat{m}_{ds}^k. \tag{16}$$

From here, we get the total overall misreported import value for each importer by taking absolute values of equation 16, leading to

$$\tilde{M}_d^K = \sum_{k=1}^{K} \sum_{s=1}^{S} |\tilde{m}_{ds}^k|. \tag{17}$$

Next, to derive an overall import misreporting index (IMI_d^m), we calculate

$$IMI_d^m = \frac{\tilde{M}_d^K}{\tilde{M}_d^K + M_D^K}. \tag{18}$$

Finally, we can construct import under- and import over-reporting indices via

$$IUI_d^m = \frac{\underline{M}_d^K}{\underline{M}_d^K + M_d^K} \tag{19}$$

and

$$IOI_d^m = \frac{\overline{M}_d^K}{\overline{M}_d^K + M_d^K}. \tag{20}$$

Overall, this gives us three distinct import misreporting indices: (i) the overall import misreporting index (IMI_d^m), (ii) the import under-reporting index (IUI_d^m), and (iii) the import over-reporting index (IOI_d^m).

3.2.3 Trade Misreporting Index (*TMI*)

Depending on the underlying research question, one may sometimes be interested in misreporting exports or imports and over- or under-reporting in either domain. For example, if one was interested in questions related to tariff evasion, the import under-reporting index may be of particular interest. In turn, if we were studying the potential abuse of export subsidies, the export over-reporting index may be most appropriate to consider.

However, in its most general context researchers may be interested in an overall index that describes the degree of trade misreporting by a country in a given year. Following our methodology laid out in the previous pages, we can derive a trade misreporting index of country i in year t (TMI_{it}) via

$$TMI_{it} = \frac{\tilde{X}_s^K + \tilde{M}_d^K}{(X_s^K + M_d^K) + (\tilde{X}_s^K + \tilde{M}_d^K)}. \tag{21}$$

This provides our seventh and final index to measure trade misreporting. With these concepts in mind, we now turn to the data to illustrate the respective indices, followed by a country case study and an application of one of the developed indices.

4 The Index in Practice

4.1 Trade Data

We retrieve trade data using the commonly employed World Integrated Trade Solution database ($WITS$), which is derived from the United Nations International Trade Statistics Database (UN Comtrade).[10] Specifically, we incorporate bilateral trade data

[10]For more detailed information about the UN Comtrade data collection, coding, valuation, and processing system, we refer to the United Nations International Trade Statistics Knowledgebase, available

reported by 160 WTO members at the HS 4-digit product level from 1996-2015, using the HS1996 version (also known as HS1).[11] We consider exports and imports only, ignoring re-exports as well as re-imports. After excluding products under chapters 98 (*reserved for special uses by contracting parties*) and 99 (*commodities not specified*), this produces 58,515,054 pairs of trade data.

We want to discuss a couple of characteristics and definitions any researcher needs to face when dealing with trade data. First, one could focus on aggregated or disaggregated trade data to explore misreported trade.[12] We employ disaggregated data at the HS 4-digit level because a country could misreport export *and* import products, which may cancel out in aggregate. Therefore, aggregated numbers would neither allow us to isolate the extent of misreporting nor could we distinguish between over- and under-reporting of exports or imports.

Second, we select the HS 4-digit level over the HS 6-digit level because misclassifications into another 6-digit bin remain quite possible and such misclassifications could theoretically bias our indices. To see this, consider our coffee example: The HS 2-digit level identifies *Coffee, Tea, Maté, and Spices*; the 4-digit level considers *Coffee, whether or not roasted or decaffeinated*; the 6-digit level identifies *Coffee, not roasted and*

under https://unstats.un.org/unsd/tradekb/Knowledgebase/50075/What-is-UN-Comtrade. The International Monetary Fund (IMF), the World Bank, the Food and Agriculture Organisation (FAO), and the International Trade Center (ITC) also publish and disseminate trade data on an annual basis. We use UN Comtrade as our single source of trade data since it is considered to be the most comprehensive and primary source of international trade statistics (e.g., see Chatham House, 2018).

[11] Information on the Harmonized Commodity Description and Coding Systems (HS) can be found at the World Customs Organization website under http://www.wcoomd.org/en/topics/nomenclature/overview.aspx and the World Integrated Trade Solution (WITS) website under https://wits.worldbank.org/wits/wits/witshelp/content/Annex/Annex1.About_WITS_HS_Combined.htm.

[12] For example, Egger and Larch (2012) and Kellenberg and Levinson (2016) use aggregated trade data from UN Comtrade and Buehn and Eichler (2011) use aggregated trade figures from IMF's Directions of Trade Statistics (DOTS). Ferrantino et al. (2012), Fisman and Wei (2004), and Mishra et al. (2008) use HS-6 digit data from UN Comtrade, whereas Ferrantino and Wang (2008) use 8-digit trade data for China and Hong Kong from the Customs General Administration of China and the Census and Statistical Department of Hong Kong, respectively. Ferrantino and Wang (2008) employ 6-digit data from USITC's Oracle database to analyse discrepancies in reported trade data. Javorcik and Narciso (2017) also use HS 6-digit trade data from UN Comtrade.

not decaffeinated. It is quite conceivable that one party could mistake roasted for decaffeinated coffee (or vice versa), whereas it is more difficult to mistake coffee for tea. Of course, one could easily exploit more (or less) disaggregated levels of classifications in deriving our indices and we refer to Section A.2 for a more detailed explanation of why we choose the 4-digit level.

Third, to separate out insurance-and-freight costs from CIF (cost, insurance and freight price) import values, we follow the conversion factor of six per cent suggested by the IMF in March 2017 (Marini et al., 2018; Miao and Fortanier, 2017) and adjust all import values to make them comparable to reported FOB (from free-on-board price) export values.[13] Nevertheless, we derive virtually identical results when employing the traditional conversion factor of 1.1 (see Section A.3).

Fourth, the role of entrepôt trade has been investigated with respect to discrepancies in reported trade data (e.g., see Feenstra et al., 1999) and we need to carefully ensure that our empirically derived indices are not driven by such phenomena. Indeed, our conclusions only change marginally once we address those issues. For example, if we consider Hong Kong (the largest entrepôt worldwide) and China as one country in constructing our misreporting indices, the correlation coefficient with the baseline misreporting indices remains at 0.99. Thus, although the role of entrepôt trade may affect a couple of individual countries, it does not meaningfully affect our indices. Nevertheless, our methodology can easily be adjusted to incorporating particular entrepôt cases.

Finally, in alternative estimations, we check whether our indices are influenced by

[13] UN Comtrade reports import data on a CIF basis, while exports are reported as FOB values. Some studies employ an average adjustment factor of 1.1, as suggested by the IMF, 1993 (e.g., see Buehn and Eichler, 2011, and UNCTAD, 2016). However, the economics and transport literature describes a declining trend in transport cost over the decades (see Hummels, 2007, and Timmer, M. P. (Ed), 2012, among others), leading to the March 2017 IMF conversion suggestion of six per cent (Marini et al., 2018; Miao and Fortanier, 2017).

'neighbourhood' effects. Intuitively, some countries may naturally trade with other countries that misreport more than others, which could artificially skew their own misreporting index. For example, consider a three-country example: the US, China, and Fredonia. Imagine that the US and China report relatively accurately, whereas Fredonia is a chronic misreporter. Now, if the US only traded with China, whereas China traded with both (perhaps because of geographical proximity), China would incorrectly fare worse on our proposed measure. To account for such concerns, we also derive the proposed indices with intra-OECD high-income countries reported trade statistics only. The corresponding results show consistent results in that the respective index values for the OECD countries are not significantly different from their misreporting indices when estimated using their entire trade relationships with all countries (see Section A.4). Although this exercise does not fully resolve potential 'neighbourhood' effects, they provide us with some comfort that potential biases may be small (if any).

4.2 Country Rankings

Following our theoretical framework outlined in Section 3, we derive seven trade misreporting indices for each reporting country per year for the period of 1996-2015. By construction, all indices range between zero and one, where values approaching zero represent less misreporting and higher values indicate more misreporting. Table 2 reports summary statistics of the indices.[14] Although only of a rough descriptive nature, Table 2 gives us some insights about what kind of trade appears to be misreported the most. For example, misreporting exports is suggested to be globally more

[14]In Table A5, we display correlation coefficients among the respective indices, whereas Table A6 presents correlation coefficients with popular country-level variables for the interested reader. A full list of all trade misreporting indices for 160 WTO members for the 1996-2015 period can be accessed under https://farhadm.weebly.com/trade-misreporting-index.html.

prevalent than misreporting imports, with the exception of over-reporting. Similarly, under-reporting indices are larger, on average, than the over-reporting indices.

Table 2: Summary statistics of all trade misreporting indices for all countries.

Index	N	Mean	(Std. Dev.)	Min	Max
Trade misreporting index (*TMI*)	2,453	0.293	0.142	0.075	0.961
Export misreporting index (*EMI*)	2,453	0.312	0.193	0.061	0.999
Export under-reporting index (*EUI*)	2,453	0.226	0.209	0.025	0.999
Export over-reporting index (*EOI*)	2,453	0.143	0.087	0.013	0.495
Import misreporting index (*IMI*)	2,453	0.284	0.127	0.083	0.896
Import under-reporting index (*IUI*)	2,453	0.176	0.134	0.031	0.891
Import over-reporting index (*IOI*)	2,453	0.157	0.067	0.043	0.500

Table 3 lists the top and bottom ten countries for the *Trade Misreporting Index* (*TMI*) among the 127 countries for which data are available in 2015, the most recent year in our database. The results suggest Togo, Antigua and Barbuda, Panama, Afghanistan, and Malta as the biggest misreporters, whereas Canada, Peru, Chile, Mexico, and the US are the most accurate reporters of trade data. To provide a quantitative example as to what the index means in practice, consider the case of Togo. A score of 0.784 in the *TMI* indicates that for every US\$100 of reported trade, Togo misreported its trade value by approximately US\$363. This follows directly from our index calculation in equation 11 since for reporting US\$100, we get $0.784 = \frac{m}{m+100}$, which, after some simple algebra, produces $m = 363$.

Tables 4 and 5 list the respective top ten rankings for the remaining six indices, where we distinguish between under- and over-reporting of exports and imports. These distinctions provide us with more detail about how a particular country re-

Table 3: List of the top and bottom ten countries in 2015 for the trade misreporting index (*TMI*).

Top 10 Misreporting Country			Bottom 10 Misreporting Country		
Rank		Trade misreporting index	Rank		Trade misreporting index
1	Togo	0.784	118	Brazil	0.154
2	Antigua and Barbuda	0.713	119	Japan	0.148
3	Panama	0.712	120	Germany	0.144
4	Afghanistan	0.636	121	Italy	0.140
5	Malta	0.614	122	Argentina	0.137
6	Benin	0.613	123	United States	0.133
7	Kuwait	0.592	124	Mexico	0.133
8	Sierra Leone	0.561	125	Chile	0.124
9	Solomon Islands	0.494	126	Peru	0.123
10	Niger	0.481	127	Canada	0.098

ceived a high or low score on the *TMI*. For example, Togo's misreporting in 2015 is primarily driven by under-reporting of imports, and the country remains absent from all three of the top ten lists for export misreporting. Although Table 4 suggests some misreporters that may have been expected, they also produce results that are perhaps surprising at first sight. For example, export over-reporting may be much less of an issue among top offenders than export under-reporting, as indicated by the top values in either index (0.991 and 0.433; see Panels B and C of Table 4). Consequently, the ten countries that are suggested to misreport exports the most are also those who under-report exports most. Further, the top five countries in the export over-reporting category are African, whereas five of the least under-reporting exporters come from the European Union (EU). However, surprisingly, no EU country makes that list when it comes to export over-reporting. These basic descriptive characteristics of the derived indices illustrate that simply relying on development status or income levels when determining who does and does not report correctly can lead to misleading conclusions.

Table 5 turns to misreported imports. As with exports, the values of the top ten suggest that under-reporting is more of an issue than over-reporting when it comes to imports. Seven OECD nations rank among the bottom ten when it comes to misreporting imports in general, whereas the EU nations Croatia, Spain, Denmark, Portugal, the United Kingdom, Italy, and Romania are suggested to be least prone to over-reporting imports. These results are different from those for exports (see Panel C of Table 4), where EU economies remain absent from the respective list.

Finally, Table 6 explores country groups by income levels and geographical region, using data for the entire timeframe of 1996-2015. On average, high-income OECD countries misreport the least, whereas low-income countries misreport their trade values most during that 20-year timespan. Although speculative at this point, this may be reflective of a weak state of governance, more restrictive trade policies, and capacity constraints to record and report trade statistics accurately. In fact, Besley and Persson (2013) point out that the pattern of taxation often changes in the process of development from trade-based to income-based.[15] However, and perhaps surprisingly, rich non-OECD countries emerge as the second-highest trade misreporting country group and the highest export under-reporting country group. Including Kuwait, Saudi Arabia, and the United Arab Emirates, that group relies heavily on exporting oil and other natural resources. Although speculative at this point, this could hint at illicit capital outflows through export under-reporting. These findings are also commensurate with the regional average, producing the Middle East and North Africa as the

[15] Besley and Persson (2013, p.54) note that "[t]he greater reliance on trade taxes (and seigniorage) than income taxes in poor economies, which we discuss further below, has been noted and discussed by many authors – see Burgess and Stern (1993), Hinrichs et al. (1966), and Tanzi (1992), for early contributions." They further discuss how taxing trade on big ports is often easier and more feasible for a weak state than the systematic collection of income taxes which "requires major investments in enforcement and compliance structures throughout the entire economy".

Table 4: List of the top and bottom ten countries in 2015 for export misreporting.

Top 10 Misreporting Country			Bottom 10 Misreporting Country		
Rank		Index	Rank		Index
Panel A: Export misreporting index (*EMI*)					
1	Antigua and Barbuda	0.991	118	El Salvador	0.121
2	Macao	0.983	119	Bolivia	0.121
3	Kuwait	0.889	120	Germany	0.116
4	Sierra Leone	0.884	121	Mexico	0.113
5	Panama	0.841	122	Angola	0.107
6	Yemen	0.823	123	Argentina	0.104
7	Hong Kong	0.806	124	Chile	0.101
8	Saudi Arabia	0.737	125	Peru	0.100
9	Cyprus	0.707	126	Brunei	0.074
10	United Arab Emirates	0.695	127	Canada	0.068
Panel B: Export under-reporting index (*EUI*)					
1	Antigua and Barbuda	0.991	118	Mongolia	0.054
2	Macao	0.983	119	Slovak Republic	0.053
3	Kuwait	0.883	120	Poland	0.050
4	Sierra Leone	0.872	121	Czech Republic	0.049
5	Panama	0.836	122	Belgium	0.049
6	Yemen	0.810	123	Bolivia	0.047
7	Hong Kong	0.791	124	Germany	0.046
8	Saudi Arabia	0.725	125	Paraguay	0.036
9	Cyprus	0.693	126	Canada	0.035
10	United Arab Emirates	0.680	127	Brunei	0.028
Panel C: Export over-reporting index (*EOI*)					
1	Sierra Leone	0.433	118	New Zealand	0.052
2	Niger	0.420	119	Japan	0.051
3	Central African Republic	0.398	120	Chile	0.050
4	Zimbabwe	0.393	121	Macedonia	0.050
5	Zambia	0.380	122	Brunei	0.048
6	Kuwait	0.303	123	Peru	0.048
7	Afghanistan	0.301	124	Angola	0.048
8	Mozambique	0.292	125	St.Vincent and Grenadines	0.048
9	Yemen	0.288	126	Argentina	0.041
10	Hong Kong	0.276	127	Canada	0.036

Table 5: List of the top and bottom ten countries in 2015 for import misreporting.

Top 10 Misreporting Country			Bottom 10 Misreporting Country		
Rank		Index	Rank		Index
Panel A: Import misreporting index (*IMI*)					
1	Togo	0.810	118	India	0.150
2	Panama	0.694	119	Chile	0.147
3	Antigua and Barbuda	0.660	120	United Kingdom	0.145
4	Afghanistan	0.644	121	Japan	0.144
5	Malta	0.641	122	Italy	0.143
6	Benin	0.638	123	Peru	0.142
7	Sierra Leone	0.488	124	Romania	0.139
8	Kyrgyz Republic	0.461	125	Canada	0.125
9	Central African Republic	0.454	126	Botswana	0.116
10	Brunei	0.453	127	United States	0.109
Panel B: Import under-reporting index (*IUI*)					
1	Togo	0.801	118	India	0.061
2	Panama	0.681	119	Costa Rica	0.058
3	Malta	0.618	120	Peru	0.058
4	Antigua and Barbuda	0.618	121	El Salvador	0.058
5	Benin	0.610	122	Japan	0.054
6	Afghanistan	0.565	123	China	0.053
7	Kyrgyz Republic	0.415	124	United States	0.052
8	Guinea	0.383	125	Botswana	0.050
9	Cambodia	0.374	126	Mexico	0.048
10	Brunei	0.369	127	Canada	0.046
Panel C: Import over-reporting index (*IOI*)					
1	Sierra Leone	0.362	118	Croatia	0.084
2	Central African Republic	0.349	119	Spain	0.083
3	Afghanistan	0.336	120	Denmark	0.083
4	Niger	0.318	121	Portugal	0.081
5	Burkina Faso	0.280	122	Hong Kong	0.078
6	Burundi	0.274	123	United Kingdom	0.077
7	Macao	0.265	124	Botswana	0.073
8	Guyana	0.264	125	Italy	0.069
9	Solomon Islands	0.254	126	Romania	0.068
10	Uganda	0.254	127	United States	0.064

top export misreporting region. North America remains the least misreporting region, both concerning exports and imports, while Sub-Saharan Africa appears as the top import misreporting region. Figure A4 displays the top five misreported product groups (at the HS 2-digit level) during our sample period. With these descriptive data in mind, we now turn to exploring misreported trade data for China as a prominent example.

4.3 Trade Misreporting: The Case of China

The case of China has generated particular interest in the trade misreporting literature (e.g., see Feenstra et al., 1999, Fisman and Wei, 2004, and Ferrantino et al., 2012). China's enormous economic growth over the past three decades has seen the country rise to the world's largest merchandise trader in 2015. Figure 1 visualizes China's *TMI* over our sample period. Interestingly, the index begins to decline sharply right before 2000 and through to 2011, indicating a constant improvement in trade reporting relative to its trading partners. Regarding magnitude, this sizeable drop from 1998 to 2011 is equivalent to more than two-thirds of a standard deviation of the *TMI* across all countries and years. China formally joined the WTO in 2001, after a couple of years of negotiations. In theory, joining the WTO required China to liberalise much of its trading sectors, along with streamlining its trade reporting system and improving transparency. Although a range of motivations and policy responses may influence trade misreporting, China's accession to the WTO – which required a steep reduction of tariff and non-tariff barriers, a drastic overhauling of its state-owned enterprises (SOEs), a gradual opening of its financial system (e.g., see Lu and Yu, 2015, Khandelwal et al., 2013, Bajona and Chu, 2010, Prasad et al., 2005, and He et al., 2014), as well as a substantial reduction in trade policy uncertainty with respect to its

Table 6: Averages over time and by income and regional groups for different trade misreporting indices, using all data from 1996-2015.

	Trade misreporting (*TMI*)	Import misreporting (*IMI*)	Import under-reporting (*IUI*)	Import over-reporting (*IOI*)	Export misreporting (*EMI*)	Export under-reporting (*EUI*)	Export over-reporting (*EOI*)
Panel A: Averages by income groups							
High-income, OECD	0.182	0.188	0.106	0.102	0.177	0.089	0.105
High-income, non-OECD	0.364	0.318	0.212	0.162	0.444	0.378	0.155
Upper middle income	0.286	0.280	0.164	0.162	0.294	0.215	0.123
Lower middle income	0.315	0.312	0.196	0.174	0.317	0.231	0.144
Low income	0.432	0.405	0.273	0.225	0.463	0.343	0.248
Panel B: Averages by regions							
East Asia & Pacific	0.264	0.255	0.144	0.152	0.299	0.224	0.126
Europe & Central Asia	0.257	0.262	0.169	0.131	0.258	0.161	0.133
Latin America & Caribbean	0.312	0.301	0.196	0.160	0.341	0.280	0.117
Middle East & North Africa	0.349	0.276	0.163	0.160	0.418	0.353	0.147
North America	0.112	0.111	0.049	0.069	0.119	0.072	0.055
South Asia	0.260	0.269	0.142	0.170	0.252	0.172	0.111
Sub-Saharan Africa	0.382	0.373	0.233	0.219	0.399	0.285	0.211
Western Europe	0.205	0.208	0.131	0.101	0.200	0.104	0.122
World average	0.293	0.284	0.176	0.157	0.312	0.226	0.143

Notes: In Section A.6, we present average trend of trade misreporting for all countries during that period in Figure A1, whereas Figure A2 and Figure A3 display trend of trade misreporting for country groups by income level and geographical region, respectively.

trading partners (see Feng et al., 2017, and Brandt et al., 2017) – is likely to be reflected in this declining trend of the *TMI*.

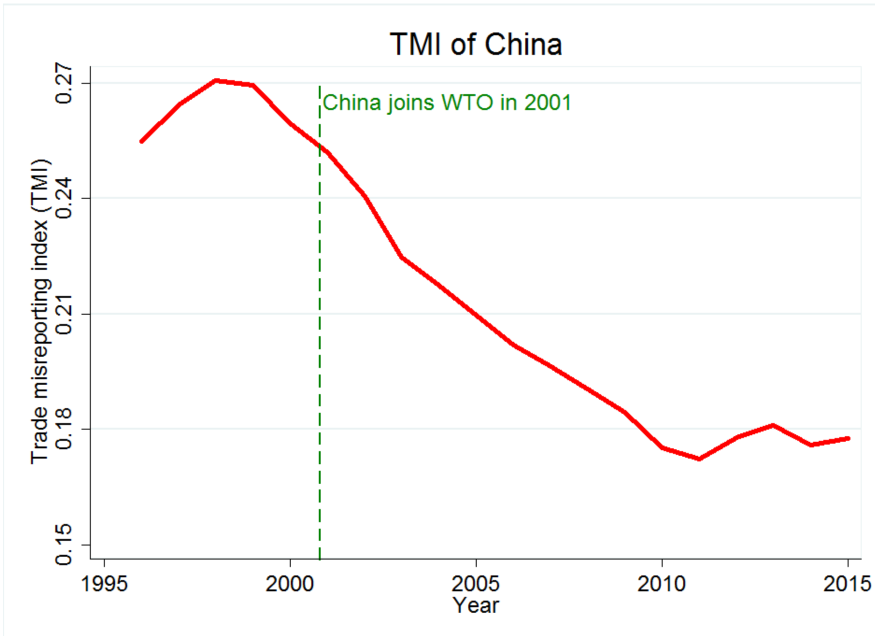

Figure 1: Trade misreporting of China from 1996 to 2015.

Further, Figure 2 illustrates China's development when it comes to under-reporting and over-reporting. Intuitively, import-overinvoicing or export under-invoicing can be used to circumvent outward capital controls, thereby transferring money abroad via official channels (e.g., see Bhagwati, 1964, 1967). In turn, foreign capital can be channelled into the country through over-invoicing of exports or under-invoicing of imports. One hypothesis that could (at least in part) explain China's changes in these indices over time is related to illicit capital flows. Recently, Chen and Qian (2016) developed extensive measures to capture the ongoing changes in China's capital control regime, using detailed information from the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions* (*AREAER*) for the 1999-2012 period. Their *de jure* and *hybrid* indices reflect a persistent process of liberalising China's capital account since 2000. Specifically, Chen and Qian (2016) report that China liberalised its capital outflow controls faster than its control on capital inflows, which may encourage outward FDI to support China's 'going global' policy initiative of 2002. Interestingly, both our import over-reporting and export under-reporting indices for China in Figure 2 exhibit a consistent downward trend since 2001. In fact, our import over-reporting index correlates positively with Chen and Qian's (2016) *de jure* and *hybrid* capital outflow control indices, with correlations of 0.90 and 0.75, respectively. Further, our export under-reporting index correlates positively with Chen and Qian's (2016) *de jure* and *hybrid* capital outflow control indices, with even stronger correlation coefficients of 0.98 and 0.93. In sum, our derived indices are consistent with the specific explanation put forth by Chen and Qian (2016).

Finally, Chen and Qian's (2016) *hybrid* index shows higher magnitudes of inflow controls than their *de jure* index. Chen and Qian (2016) report that China has experienced an episode of 'hot money' inflows since 2003 and the Chinese government's constant initiatives to restrain such capital inflows. Similarly, Ferrantino et al. (2012) suggest the possibility of 'hot money' inflows from the US into China during the 2003-2008 period. Interestingly, our export over-reporting index for China reveals a constant upward trend beginning in 2003 – an observation that is consistent with that hypothesis. However, this trend reversed from 2013 onwards, which may reflect China's sharp relaxation of its capital inflow regime during that period. We particularly notice China's new rules on FDI in late 2011, which officially allow foreigners to invest in the Chinese mainland with offshore funds.[16] China's import under-reporting index remains almost stable since 2000.

Overall, these descriptions are, of course, purely suggestive at this point. Never-

[16] For details on these measures, we refer to the Global Legal Monitor of the Library of Congress of the US (available under http://www.loc.gov/law/foreign-news/article/china-new-rules-on-foreign-direct-investment-with-renminbi/) and the IMF's AREAER dataset (available under http://www.elibrary-areaer.imf.org/Pages/ChapterQuery.aspx).

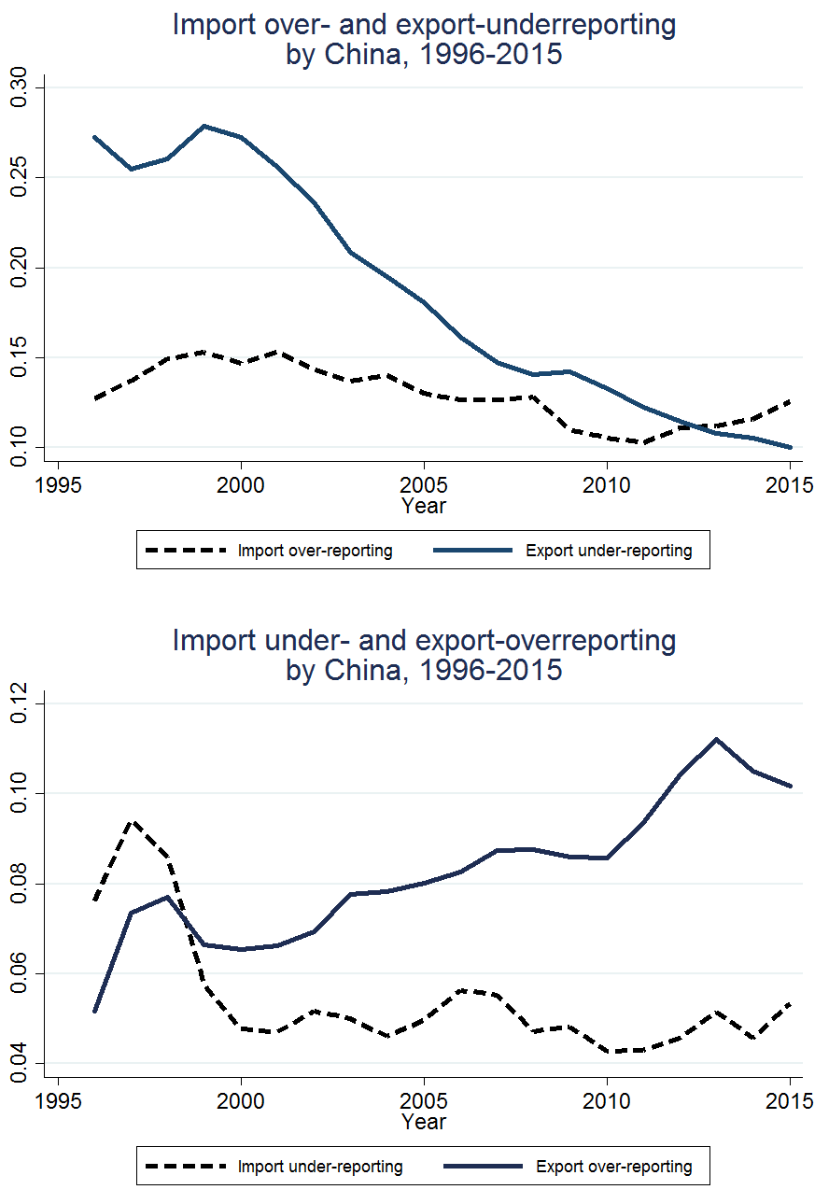

Figure 2: Different trade misreporting indices for China from 1996 to 2015.

theless, it is interesting to see that our indices show developments that are consistent with hypotheses about China's development and closely correlated with other China-specific indices. With this in mind, we now turn to an empirical application of our import under-reporting index to exploring the role of tariffs and VAT rates.

5 Empirical Application: Tariffs, VAT Rates, and Under-Reporting Imports

5.1 Setting

In this section, we provide one application of our misreporting indices, predicting the import under-reporting index (*IUI*) with tariff and VAT rates in our panel dataset. We choose to examine the under-reporting of imports because it remains the main focus of the existing literature on trade misreporting (e.g., see Javorcik and Narciso, 2008, Mishra et al., 2008, and Ferrantino et al. (2012)). Intuitively, an economic agent may try to curb their import costs by avoiding or at least minimising tariff payments – payments that are usually based on the import value. Everything else equal, we would expect import values to be more under-reported when tariff rates are high. Of course, a range of other factors may play an independent role, and we will shortly discuss how we try to control for such potentially confounding factors.

The existing literature finds empirical evidence of systematic under-reporting of imports motivated by burdensome tariffs. Bhagwati (1964) reports strong evidence of understated imports in Turkey, which are systematically correlated with tariffs and import controls; Fisman and Wei (2004) find Chinese imports from Hong Kong to be under-reported; Mishra et al. (2008) identify similar dynamics for Indian imports from its major trading partners; Ferrantino et al. (2012) suggest the same when it comes to

US imports from China. As discussed before, these studies focus on reported trade either between a pair of bilateral trading partners or between a particular country of interest and its major trading partners.

Our objective here is to examine whether our import under-reporting index produces similar conclusions as these country-specific studies. In general, the corresponding results should indicate whether import under-reporting motivated by tariff evasion is indeed a global phenomenon or these conclusions only pertain to these specific countries. In addition to tariff rates, we also investigate whether VAT rates, which are calculated and payable according to the reported import value, are positively correlated with the import under-reporting index.

5.2 Econometric Specification

We estimate a standard linear regression model, predicting the *IUI* with tariff and VAT rates in the country i and year t. To properly isolate potential relationships, we control for several other variables that may independently affect the reporting of imports. Further, we account for the country- and year-fixed effects to control for any country- and time-specific phenomena that could drive under-reported imports. For instance, a country's geography or regular trading partners (perhaps stemming from historical connections, such as colonialism) may systematically influence the reporting of trade data. Similarly, persistent cultural and institutional characteristics could affect misreporting. With respect to time-specific unobservables, global recessions or booms could systematically drive global misreporting rates. Two-way fixed effects can isolate our analysis from any such dynamics. Formally, we estimate

$$IUI_{i,t} = \beta_0 + \beta_1 \left(Tariff\right)_{i,t} + \beta_2 \left(VAT\right)_{i,t} + \mathbf{X}_{i,t}\gamma + \alpha_i + \omega_t + \varepsilon_{i,t}, \tag{22}$$

where $URI_{i,t}$ refers to the import under-reporting index for country i in year t. $\left(Tariff\right)_{i,t}$ measures the trade-weighted applied tariff rates for all products from all source countries to each importing country i at time t, whereas $\left(VAT\right)_{i,t}$ represents the value added tax rates applicable to all imports by the importing country. $\mathbf{X}_{i,t}$ constitutes a vector of other observable country characteristics that may carry an independent effect on reporting behaviour. Specifically, we include measures for (i) capital account openness, (ii) trade openness, (iii) democracy, and (iv) corruption. Bhagwati (1964) and Ferrantino et al. (2012) discuss the possibility of misreporting of trade data as one of several methods to avoid capital controls, while Fisman and Wei (2009) report a positive correlation between corruption and trade data discrepancies. Kellenberg and Levinson (2016) also employ capital controls and corruption while explaining misreported trade and tariff evasion. Further, we control for trade openness and democracy since higher levels of integration with the global trade network and a more democratic system, associated with more inclusive political institutions and the prevalence of the rule of law, may well form independent drivers of misreporting trade numbers. In addition, country- and time-fixed effects are captured by α_i and ω_t, whereas $\varepsilon_{i,t}$ represents the usual error term. Throughout our estimations, we report robust standard errors, as well as standard errors clustered at the country level. Finally, we multiply our import under-reporting index by 100 to facilitate the quantitative interpretation of coefficients.

5.3 Data Sources for Control Variables

We access data on corruption levels from the Corruption Perceptions Index (CPI, provided by Transparencey International, 2017).[17] From 1995 to 2011, the CPI ranged

[17] The CPI has been developed by Transparency International since 1995, providing "country level annual corruption scores" based on the perceived levels of corruption, as determined by expert assess-

from zero to ten, but since 2012 the index ranges from zero to 100, following an update in methodology. We rescale earlier data to match the post-2011 range from zero to 100. Note that the CPI codebook specifically mentions this switch in measurement comes because researchers should *not* compare data before 2012 with those since then. In our case, however, accounting for time-fixed effects accounts for such measurement issues. Nevertheless, all our findings are consistent when excluding the CPI.

GDP per capita (measured in constant 2010 US$), trade-weighted applied tariff rates, and VAT rates are collected from the World Bank's "World Development Indicators" (The World Bank, 2018). For capital account openness, we access the Chinn-Ito index (*KAOPEN*), which measures a country's degree of capital account openness.[18] The scale of the *KAOPEN* index ranges from the "most financially open" value of 2.37 to the "least financial open", scored at -1.90. Additionally, we use the *polity2* variable from the Polity IV dataset to measure the country's degree of democracy in the respective year (Marshall and Jaggers, 2017). This variable captures the regime authority spectrum on a 21-point scale ranging from -10 (complete autocracy) to +10 (consolidated democracy). Table A7 presents summary statistics of all covariates.

5.4 Empirical Results

The results from our econometric specifications are reported in Table 7. We display robust standard errors in parentheses under the respective coefficients and standard errors clustered at the country level in brackets. We begin by examining the univariate relationships between the import under-import reporting index and our two variables of interest: Tariff and VAT rates. The corresponding coefficients are displayed in

ments and opinion surveys.

[18]The *KAOPEN* index was initially introduced by Chinn and Ito (2006) and the latest update covers the time period of 1970-2015 for 182 countries.

columns (1) and (2). Regression (3) then considers tariff and VAT rates simultaneously as predictors of the *IUI*. In column (4), we introduce our set of control variables, while columns (5) and (6) incorporate country- and year-fixed effects. To facilitate the comparison of results across regressions, we only employ observations in which data for all variables are available. Nevertheless, all results are robust when using all available observations for the respective specifications.

The results concerning tariff and VAT rates provide strong support for the hypothesis that an increase in either rate is associated with a significant increase in the under-reporting of imports. These results emerge for all six specifications and are consistent with the discussed country-specific studies. It may also be useful to consider the derived magnitudes of the effects. In the most complete specification (column 6), the implied magnitudes for tariff and VAT rates are quite comparable. A one standard deviation increase in tariff rates (equivalent to approximately 4.6 points) would be associated with a 0.9 point rise in the import under-reporting index, on average. (Remember that the *IUI* is scaled to range from zero to 100.) When it comes to VAT rates, a one standard deviation increase (equivalent to 5.3 points) corresponds to a 1.1 point increase in the import under-reporting index.

Finally, we can put these magnitudes in context via a simple back-of-the-envelope calculation. For example, what would a 2 per cent change in the *IUI* for, say, India? In 2015, the *IUI* value for India was 0.060, meaning India is suggested to have under-reported its imports by approximately US$6.4 for every US$100 reported. In 2015, the total reported imports of India were US$390,745 million, and the country's trade-weighted average tariff rate was 6.35 per cent. Therefore, an estimated $1.6 billion of Indian tariff revenue is suggested to be lost due to under-reporting of imports. Consequently, a hypothetical 2 per cent decrease in the *IUI* value would correspond to an increase of around US$550 million tariff revenue for the Indian government in

Table 7: Predicting the import under-reporting index (*IUI*) with tariff and VAT rates.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Import under-reporting index (mean=14.90)						
Tariff	0.654		0.733	0.548	0.222	0.195
	(0.097)***		(0.100)***	(0.104)***	(0.084)***	(0.087)**
	[0.261]**		[0.263] ***	[0.257]**	[0.084]***	[0.087]**
VAT		0.317	0.411	0.423	0.192	0.202
		(0.057)***	(0.064)***	(0.066)***	(0.065)***	(0.064)***
		[0.153]**	[0.162]**	[0.165]**	[0.065]***	[0.064]***
Capital account openness				-0.064	-0.263	-0.274
				(0.254)	(0.631)	(0.634)
				[0.589]	[0.631]	[0.634]
Trade openness				0.038	0.014	0.016
				(0.005)***	(0.020)	(0.025)
				[0.016]**	[0.020]	[0.025]
Democracy (polity2)				-0.122	0.085	0.064
				(0.089)	(0.143)	(0.137)
				[0.232]	[0.143]	[0.137]
Corruption (CPI)				-0.093	-0.023	-0.008
				(0.014) ***	(0.049)	(0.049)
				[0.037]**	[0.049]	[0.049]
Country-fixed effects					Yes	Yes
Year-fixed effects						Yes
# of countries	107	107	107	107	107	107
# of years	10	10	10	10	10	10
Observations	1,344	1,344	1,344	1,344	1,344	1,344
R-squared	0.069	0.024	0.108	0.173	0.145	0.111

Notes: The dependent variable is the import under-reporting index, as defined in equation 22. Robust standard errors are displayed, whereas standard errors clustered by reporting country are listed in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2015.

6 Conclusion

This paper proposes a novel methodology to estimate a country's degree of trade misreporting. Our methodology does not require any ad-hoc assumptions about who may or may not report accurately; rather, it incorporates the full range of available data to compute the trade reporting patterns of a country with all of its trading partners in a given period. We use this information to weight each reported trade entry and derive seven specific trade misreporting indices, capturing under- and over-reporting of trade, exports, and imports, as well as total trade misreporting.

After laying out the theoretical derivation, we apply our measurement technique to bilateral annual trade data from 1996-2015, covering over 58 million trade entries at the HS 4-digit level, accounting for approximately 98 per cent of world merchandise trade. To our knowledge, this constitutes the first systematic trade misreporting indices that are comparable across countries and over time, as well as independent of *a priori* definitions about countries' reporting accuracies. In a descriptive analysis of the associated country rankings, we find low-income countries to misreport relatively more, possibly reflecting their capacity constraints and overall restrictive policy regimes, as well as weak governance and institutional quality. Indeed, previous research has shown that as countries develop, they usually move from taxing trade to taxing income (e.g., see Besley and Persson, 2013). We find that emerging economies, including countries exporting primary resources, are more likely to over-report exports – an indication for illicit capital flight. We then specifically analyse the prominent case of China's trade data, and our indices suggest the country's trade reporting started to improve substantially when negotiations over joining the WTO began in the late 1990s. Further, China's relaxation of its restrictive capital control policies coincides with a fall in the country's export under-reporting.

Finally, we present an empirical analysis of import under-reporting, using our panel data set of 107 countries from 1996-2015. Economic intuition, as well as several country-specific studies, suggest that larger tariff or VAT rates should increase importers' incentives to under-report in order to avoid taxation. Indeed, our results provide evidence consistent with that hypothesis on a global level, even after accounting for a list of potentially confounding factors, as well as country- and year-fixed effects.

Beyond their specific implications, we see these findings, as well as the case study of China, as prominent applications to illustrate the capabilities of our derived indices for future research. For example, we hope that our indices can be of value for empirical researchers interested in a better understanding of the determinants and consequences of misreported trade data. For example, the indices may be used to study a range of trade policy analyses, such as (i) estimating the welfare effects of trade facilitation programs (e.g., tariff liberalization or preferential trading arrangements), (ii) devising effective export support and capital control programs, or (iii) supplementing bilateral and multilateral trade negotiations and foreign policymaking, to name just a few. Naturally, we do not claim these indices to be perfect. However, we hope they provide a useful starting point to empirical studies on trade misreporting.

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A Appendix

A.1 Example of Mirror Import Data

Table A1: Mirror trade flow reported by importer Tunisia (d_1) and *all* source countries: Brazil (s_1), Bangladesh (s_2), and Australia (s_3).

	HS-4 code	Destination	Source	Import value ($000)	Export value ($000)	Absolute Reporting distance ($000)
$(d_1 \rightleftharpoons s_1)$	0110	Tunisia (d_1)	Brazil (s_1)		15	15
	0806	Tunisia (d_1)	Brazil (s_1)		20	20
	0901	Tunisia (d_1)	Brazil (s_1)	60	100	40
	4040	Tunisia (d_1)	Brazil (s_1)	50	40	10
	5050	Tunisia (d_1)	Brazil (s_1)	40	50	10
	6060	Tunisia (d_1)	Brazil (s_1)	25		25
	7009	Tunisia (d_1)	Brazil (s_1)	10		10
	8080	Tunisia (d_1)	Brazil (s_1)	5		5
	8(3)	6(3)	5(3)	190(150)	225(190)	135
$(d_1 \rightleftharpoons s_2)$	1010	Tunisia (d_1)	Bangladesh (s_2)	20		
	2020	Tunisia (d_1)	Bangladesh (s_2)	40	60	20
	3030	Tunisia (d_1)	Bangladesh (s_2)	60	80	20
	4040	Tunisia (d_1)	Bangladesh (s_2)	80	100	20
	5050	Tunisia (d_1)	Bangladesh (s_2)	100	90	10
	6060	Tunisia (d_1)	Bangladesh (s_2)		100	
	7070	Tunisia (d_1)	Bangladesh (s_2)		75	
	8080	Tunisia (d_1)	Bangladesh (s_2)		20	
	8(4)	5(4)	7(4)	300(280)	525(330)	285
$(d_1 \rightleftharpoons s_3)$	2020	Tunisia (d_1)	Australia (s_3)	10		10
	3030	Tunisia (d_1)	Australia (s_3)	150	300	150
	4040	Tunisia (d_1)	Australia (s_3)	120	100	20
	5050	Tunisia (d_1)	Australia (s_3)	110	100	10
	7009	Tunisia (d_1)	Australia (s_3)		80	80
	8080	Tunisia (d_1)	Australia (s_3)		30	30
	6(3)	4(3)	5(3)	390(380)	610(500)	300
$(d_1 \rightleftharpoons s_n, n = 3)$	22(10)	14(10)	16(10)	880(810)	1,360(1,020)	720

Notes: Both imports and exports are considered here in comparable FOB values to eliminate discrepancies resulted from CIF and FOB price reportings by the importer and the exporters, respectively.

We can derive the *import weighting factor* (*IWF*) following equation 6 presented in Section 3.1.2. Using the import data from Table A1, we derive Tunisia's IWF in this example is $1 - \frac{720{,}000}{880{,}000 + 1{,}360{,}000} = 0.679$.

A.2 Misreporting or Misclassification? Using HS 4-Digit Product Level Trade Data

The Harmonized Commodity Description and Coding System (or simply HS), developed, maintained, and monitored by the World Customs Organization (WCO) was introduced in 1988 and has since been adopted by most countries worldwide as a basis for collecting international trade statistics. It currently covers more than 98 per cent of international merchandise trade globally and national customs authorities of more than 200 WCO member countries.[19] The HS comprises approximately 5,300 product descriptions that appear as headings and subheadings, arranged in 99 chapters, grouped in 21 sections.

The uniform product classification across countries only goes down to HS 6-digit level of disaggregation, while national product classifications often extended up to 8 to 10 digit level (e.g., India and Singapore use 8-digit product classification, while China, UK and USA use 10-digit national product classification.) Thus, internationally available trade data comparable across countries allow us to use at best HS 6-digit disaggregated data for measuring trade misreporting. One might tend to attribute a portion of discrepancies in reported bilateral international trade data to different product classifications used by different countries and the possibility of unintentional misclassification of products by national customs authorities. This demands a brief discussion of HS Nomenclature and Classification of Goods.

Table A2 shows an example of the HS nomenclature. The six digits HS product code can be broken down into three parts. The first two digits (HS 2-digit) identify the chapter the goods are classified in, e.g., 09 corresponds to 'Coffee, Tea, Maté, and Spices'. The chapter is further divided by adding two digits (HS 4-digit) to identify

[19] As per the WCO website, accessed on 3 November 2017; available under http://www.wcoomd.org/en/topics/nomenclature/overview/what-is-the-harmonized-system.aspx

groupings within that chapter, e.g., 09.01 is associated with 'Coffee, whether or not roasted or decaffeinated'. Finally, the next two digits (HS 6-digit) are even more specific, e.g., 09.01.11 identifies 'Coffee, not roasted and not decaffeinated'. Up to the HS 6-digit level, all countries classify products in the same way. Thus, while the probability of unintentional misclassification is not completely ruled out (mix-up between coffee, not roasted and roasted, or not decaffeinated and decaffeinated) at the HS 6-digit level, there should not be any such unintentional misclassification at the HS 4-digit level (since coffee and tea are completely different products). Therefore, to avoid potential issues of 'unintentional misclassification' of products by some countries, our analysis focuses on the HS 4-digit product level of disaggregation.

Table A2: An example of HS product classification by the WCO: First two headings of Chapter 9.

Chapter	Heading	Sub heading (HS Code)	Product description
09			Coffee, tea, maté and spices
	09.01		Coffee, whether or not roasted or decaffeinated; coffee husks and skins; coffee substitutes containing coffee in any proportion.
			- Coffee, not roasted:
		0901.11	- - Not decaffeinated
		0901.12	- - Decaffeinated
			- Coffee roasted:
		0901.21	- - Not decaffeinated
		0901.22	- - Decaffeinated
		0901.90	- Other
	09.02		Tea, whether or not flavoured.
		0902.10	- Green tea (not fermented) in immediate packings of a content not exceeding 3 kg
		0902.20	- Other green tea (not fermented)
		0902.30	- Black tea (fermented) and partly fermented tea, in immediate packings of a content not exceeding 3 kg
		0902.40	- Other black tea (fermented) and other partly fermented tea

Notes: The 2012 edition of the WCO HS Nomenclature is available at http://www.wcoomd.org/en/topics/nomenclature/instrument-and-tools/hs_nomenclature_previous_editions/hs_nomenclature_table_2012.aspx.

Further, while the WCO reviews and amends the HS every five years, these revisions mainly targeted the fine-tuning and ensure better coverage of trade statistics at the HS-6 level.[20] Therefore, by focusing on the HS 4-digit product level we also alleviate concerns about all countries potentially not reporting their trade data using the same version of the HS nomenclature.

A.3 Using Alternative CIF/FOB Conversion Factors

Since the use of IMF recommended 6 percent CIF/FOB conversion may still leave some doubts, as this estimate is also based on flawed (misreported) data, and one would argue it is useless to impose such an average number since transport and insurance widely varies across product categories, trading partners including its distance from the counterparts and mode of transports. To check the sensitivity of our estimated indices to the use of CIF/FOB conversion factor, we test our index estimation with the traditional factor of 1.1. However, this exercise does not have any significant effect on our original indices apart from some trivial changes in the index values (see for example Table A3). This is also reflected in the correlation coefficients with our original indices, which are around 0.99 for overall misreporting index as well as other sub-indices.

[20]For example, the HS Nomenclature 2017 Edition includes 233 sets of amendments, mostly featuring the environmental and social issues of global concern. For a detailed discussion on the changes introduced in the 2017 edition, we refer to http://www.wcoomd.org/en/topics/nomenclature/instrument-and-tools/hs-nomenclature-2017-edition/amendments-effective-from-1-january-2017.aspx.

Table A3: Comparison of overall trade misreporting index (*TMI*) estimated using different CIF/FOB conversion factor for top and bottom ten countries in 2015.

Top 10 Misreporting Country				Bottom 10 Misreporting Country			
Rank		*TMI* using CIF/FOB 1.06	*TMI* using CIF/FOB 1.1	Rank		*TMI* using CIF/FOB 1.06	*TMI* using CIF/FOB 1.1
1	Togo	0.784	0.788	118	Brazil	0.154	0.153
2	Antigua and Barbuda	0.713	0.717	119	Japan	0.148	0.146
3	Panama	0.712	0.719	120	Germany	0.144	0.148
4	Afghanistan	0.636	0.640	121	Italy	0.140	0.144
5	Malta	0.614	0.620	122	Argentina	0.137	0.137
6	Benin	0.613	0.620	123	United States	0.133	0.135
7	Kuwait	0.592	0.591	124	Mexico	0.133	0.135
8	Sierra Leone	0.561	0.563	125	Chile	0.124	0.124
9	Solomon Islands	0.494	0.490	126	Peru	0.123	0.124
10	Niger	0.481	0.481	127	Canada	0.098	0.106

A.4 Accounting for 'Neighbourhood' Effects

One of the key characteristics of our trade misreporting indices is that they are non-discriminatory, i.e., they are free from *a priori* assumptions about any one country reporting more accurately than another. One concern of our method relates to the possibility of 'neighbourhood' effects via which some countries may naturally trade with notorious misreporters whereas another does not. We provide a corresponding example at the end of Section 4.1, focusing on a three-country scenario of the US, China, and Fredonia. This is a legitimate concern. We conduct one robustness check that aims to address this concern. Specifically, we calculate our respective indices using intra-OECD reported trade statistics only for the high-income OECD countries. [21] Overall, as our results have shown, the OECD countries are among the best reporters. If the derived index values were indeed much different to those for the same OECD

[21]Counties included in High-income OECD country group are: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Rep., Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, and United States. [As per OECD country classification 2018, accessed on 06-12-2018; available under: https://www.oecd.org/trade/xcred/2018-Internet-table-2-english-as-of-27-july-2018.pdf]

nations when we account for trade including non-OECD countries, that would be an indication for such 'neighbourhood' effects to present a serious problem.

Outcomes of this exercise are presented in Table A4. We find that the misreporting indices for high-income OECD countries estimated using restricted trade data among them are not significantly different from their misreporting indices when calculated for their entire trade relations with all trading partners. This provides us with some reassurance that such 'neighbourhood' effects are unlikely to systematically bias our derived indices.

Table A4: Comparing misreporting indices when only considering intra high-income OECD countries trade versus our benchmark misreporting indices.

Index:	Overall trade misreporting	Import misreporting	Import under-reporting	Import over-reporting	Export misreporting	Export under-reporting	Export over-reporting
Correlation coefficients	0.94	0.87	0.85	0.88	0.97	0.97	0.96

A.5 Correlations with Common Macroeconomic Indicators and Correlations between the Indices

Table A5 provides simple correlations among the misreporting indices, and Table A6 displays correlation coefficients between all seven misreporting indices and most common macroeconomic indicators including population size, GDP per capita, a democracy score (using the *polity*2 variable from the Polity IV indicators), corruption levels, capital account openness, and trade openness.

Table A5: Correlation coefficients among different trade misreporting indices.

Index:	Trade misreporting	Import misreporting	Import under-reporting	Import over-reporting	Export misreporting	Export under-reporting	Export over-reporting
Trade misreporting	1.00						
Import misreporting	0.88^{***} (0.00)	1.00					
Import under-reporting	0.81^{***} (0.00)	0.92^{***} (0.00)	1.00				
Import over-reporting	0.60^{***} (0.00)	0.67^{***} (0.00)	0.35^{***} (0.00)	1.00			
Export misreporting	0.89^{***} (0.00)	0.64^{***} (0.00)	0.57^{***} (0.00)	0.47^{***} (0.00)	1.00		
Export under-reporting	0.84^{***} (0.00)	0.60^{***} (0.00)	0.58^{***} (0.00)	0.38^{***} (0.00)	0.97^{***} (0.00)	1.00	
Export over-reporting	0.57^{***} (0.00)	0.44^{***} (0.00)	0.30^{***} (0.00)	0.50^{***} (0.00)	0.60^{***} (0.00)	0.39^{***} (0.00)	1.00

Note: P-values are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Correlation coefficients between trade misreporting indices and common macroeconomic indicators on the country level.

Index/ Macroeconomic indicators	Trade misreporting	Import misreporting	Import under-reporting	Import over-reporting	Export misreporting	Export under-reporting	Export over-reporting
Population size (log)	-0.40***	-0.42***	-0.32***	-0.40***	-0.37***	-0.36***	-0.17***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita (log)	-0.39***	-0.44***	-0.31***	-0.51***	-0.27***	-0.20***	-0.37***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Democracy (polity2)	-0.39***	-0.31***	-0.18***	-0.42***	-0.39***	-0.37***	-0.28***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Corruption (CPI)	-0.32***	-0.35***	-0.24***	-0.39***	-0.22***	-0.20***	-0.20***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Capital account openness	-0.26***	-0.28***	-0.19***	-0.33***	-0.20***	-0.17***	-0.16***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Trade openness	-0.10***	-0.10***	-0.11***	-0.00	0.15***	0.13***	0.09***
	(0.00)	(0.00)	(0.00)	(0.95)	(0.00)	(0.00)	(0.00)

Note: P-values are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.6 Trends of Trade Misreporting

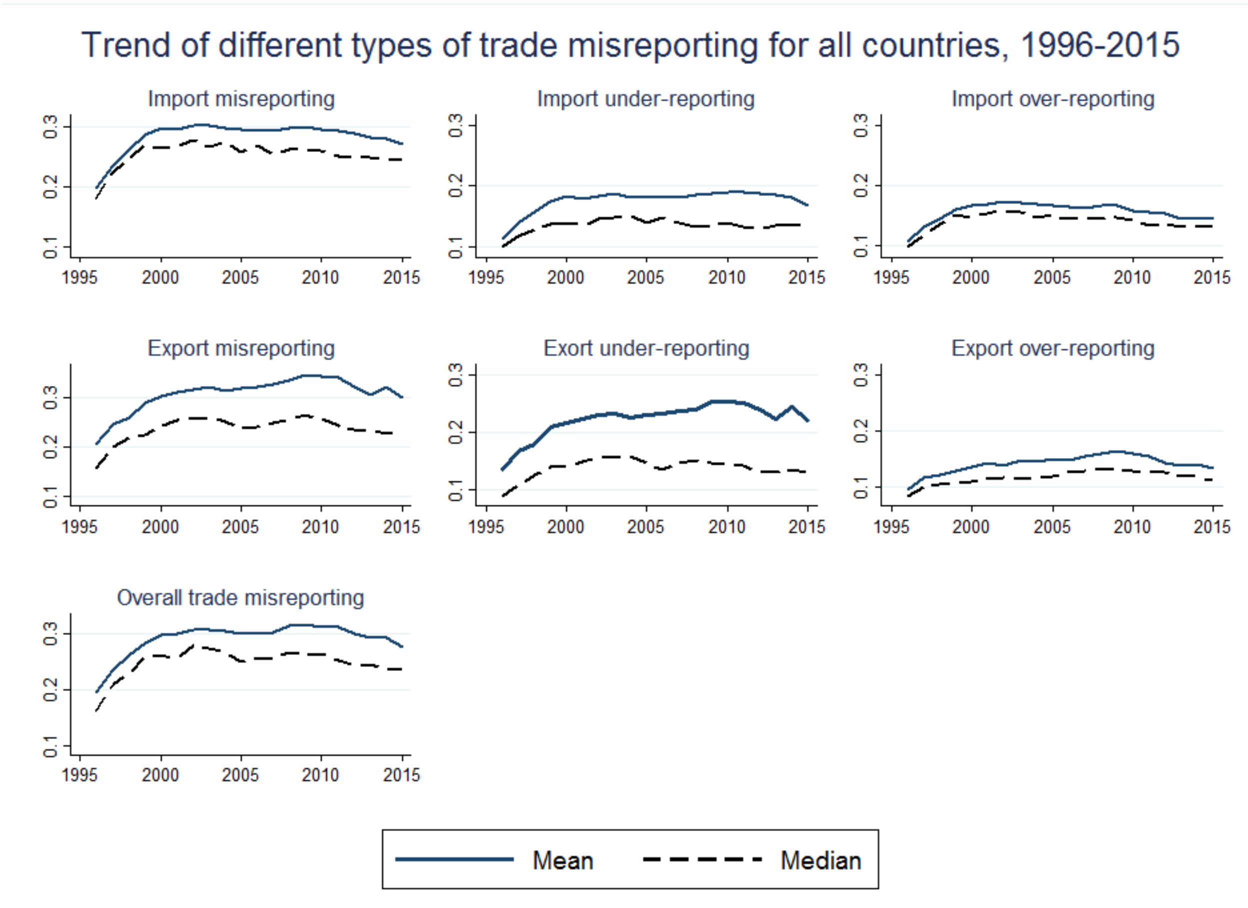

Figure A1: Trend of different types of trade misreportings for 160 WTO members, 1996-2015

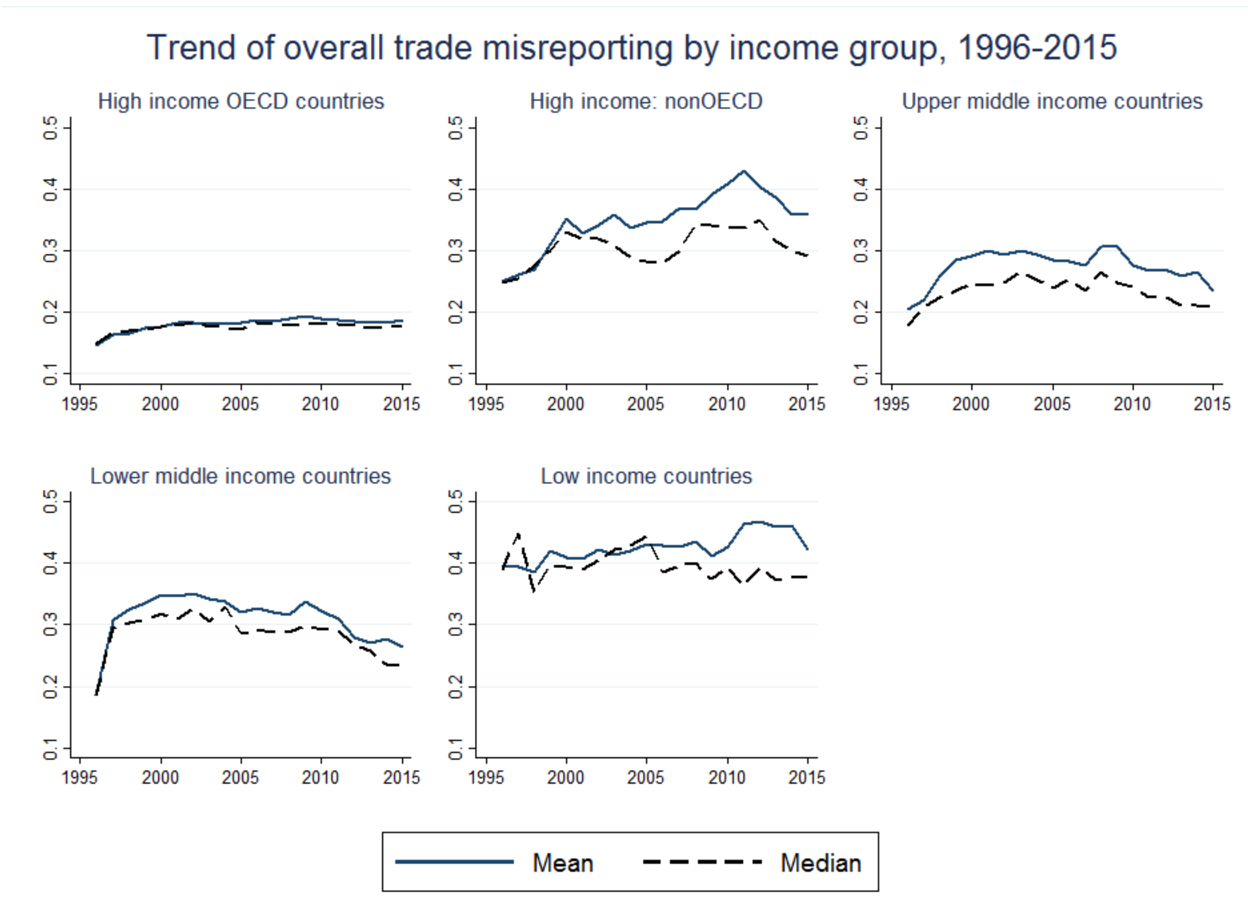

Figure A2: Trend of overall trade misreporting by income groups, 1996-2015

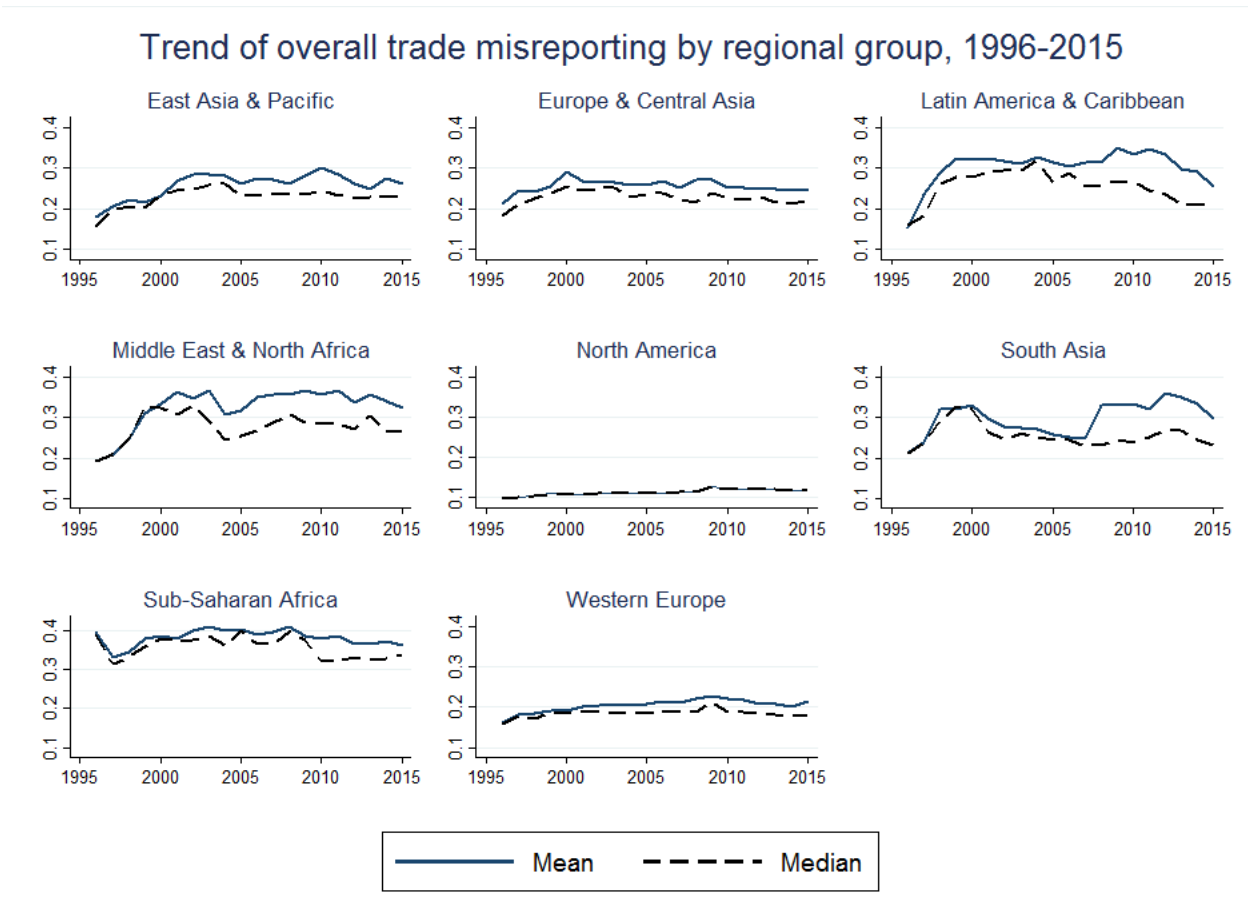

Figure A3: Trend of overall trade misreporting by regional groups, 1996-2015

A.7 Which Products are Most Prone to Trade Misreporting?

It would be further analyse which products are most prone to trade misreporting globally using our methodology. Taking misreported export and import values for each HS 4-digit product per country and year from equation 9 and equation 16 in Section 3, we compute misreporting indices for each HS 2-digit product groups using similar specifications used for computing country-specific indices. This exercise finds quite interesting results. The top five misreported product groups (at HS 2-digit product groups known as 'Chapter') were Ships, boats and floating structures (Chapter 89), Arms and ammunition, parts and accessories thereof (Chapter 93), Works of art; collectors' pieces and antiques (Chapter 97), Aircraft, spacecraft and parts thereof (Chapter 89) and Nickel and articles thereof (Chapter 75) during the last two decades as presented in Figure A4.

Arms and ammunition are naturally expected to be among the most misreported product groups, while Fisman and Wei (2009) presented strong empirical evidence of illicit trade of cultural property and antiques. The appearance of ships and aircraft among the top misreported product groups may be not that surprising as both these product groups involve largely government purchases suggesting a possibility of large-scale public corruption.

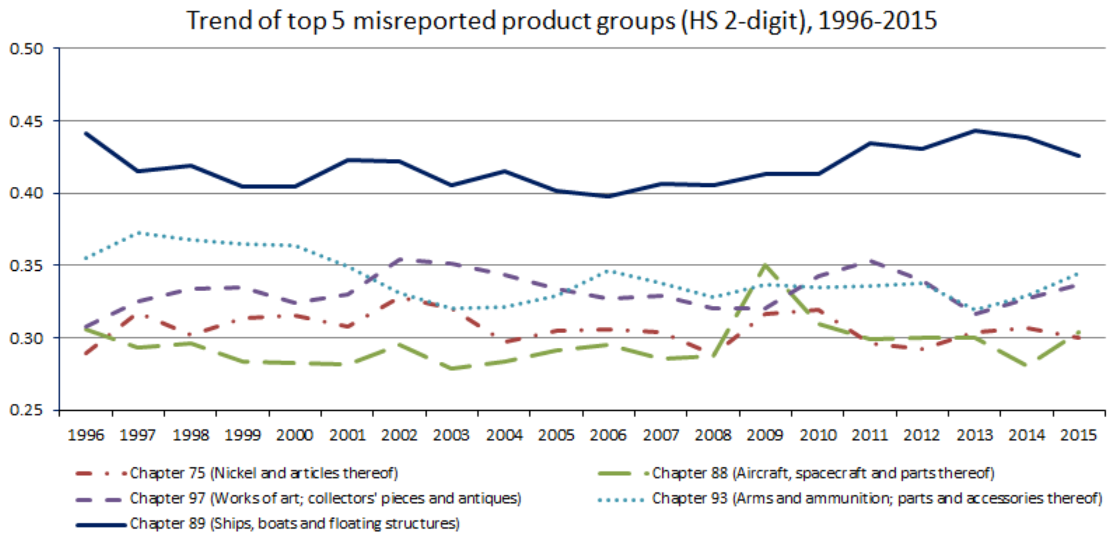

Figure A4: Top 5 misreporting product groups, 1996-2015

A.8 Summary Statistics of Data employed in Econometric Application

Table A7: Summary statistics of additional covariates.

Variables	Obs	Mean	Std. Dev.	Min	Max
Import under-reporting index [0 to100]	1,344	14.90	10.79	3.32	84.10
Tariff rate (applied, trade weighted mean, all products) (%)	1,344	4.64	4.33	0.00	28.55
Value added tax (VAT) rate (%)	1,344	10.65	5.30	0.05	67.74
Capital account openness [-1.90 to 2.37]	1,344	1.04	1.49	-1.90	2.37
Trade openness (trade % of GDP)	1,344	86.59	49.99	16.44	441.60
Democracy (polity2) [-10 to +10]	1,344	6.92	4.58	-9.00	10.00
Corruption (CPI) [0-100]	1,344	50.03	22.52	12.00	100.00

Note: This table is based on the sample used in the regression presented in Table 7.