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Nathan Carter Remcho
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John Rand
Department of Economics, Development Economics Research Group (DERG), University of Copenhagen, Copenhagen, Denmark.

Nathan Carter Remcho
Department of Economics, Development Economics Research Group (DERG), University of Copenhagen, Copenhagen, Denmark.

Finn Tarp
Department of Economics, Development Economics Research Group (DERG), University of Copenhagen, Copenhagen, Denmark.

Thomas Westergaard-Kabelmann
QBIS, Copenhagen, Denmark

Clement Otindo
KRA, Nairobi, Kenya

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ABSTRACT

This paper examines cross-country distributional patterns in CIF-FOB trade unit value ratios to identify risks of import undervaluation and overvaluation. Building on these patterns, we develop a Trade Fraud Risk Index (TFRI) that ranks countries by their exposure to trade fraud and allows tracking of risk over time and across sectors. Using trade unit values and trade volumes, and incorporating WTO tariff rates, we assess both the magnitude of CIF-FOB value gaps and the associated potential customs revenue losses at the HS 4-digit level. To complement the quantitative analysis, we incorporate qualitative fieldwork conducted at the Port of Mombasa in 2024, including interviews with clearing agents, CFS personnel, truck drivers, and port workers. These field insights illuminate the mechanisms through which misreporting, undervaluation, misclassification, and bribery occur in practice. The qualitative evidence helps explain how fraud persists despite improvements in Kenya's overall TFRI performance and provides context for sector-specific value gaps identified in the data. Applied to Kenya, the TFRI shows a marked improvement in trade fraud risk between 2005 and 2019, accompanied by a decline in estimated tariff revenue losses. The fieldwork findings, however, highlight persistent vulnerabilities within customs verification and inspection processes. Together, the TFRI and qualitative assessment offer actionable tools for customs administrations seeking to identify, understand, and mitigate trade fraud both internationally and domestically.

KEYWORDS

Mis-invoicing, CIF-FOB differences, trade fraud risk, Kenya

1 Introduction

International trade remains one of the most significant channels through which governments in developing economies mobilize revenue. For many low- and lower-middle-income countries, import duties, excise taxes, and value-added taxes on international trade collectively constitute a substantial proportion of total tax receipts. Yet these revenue streams are markedly vulnerable to various forms of customs manipulation and misreporting, particularly undervaluation of imports, misclassification of goods, and the exploitation of discretionary authority in customs procedures. Among these practices, the systematic undervaluation of imported goods is widely regarded as one of the most pervasive and difficult-to-detect forms of trade fraud. Because most customs administrations rely on ad valorem tariff structures, where duties are levied as a percentage of the declared value of imports, misreporting the value of goods creates an immediate and often substantial loss of public revenue.

The scale of this challenge has been extensively documented. Trade mis-invoicing is estimated to account for most measurable illicit financial flows (IFFs) in developing economies, with Global Financial Integrity (GFI) estimating that as much as 87% of IFFs stem from deliberate misreporting in international trade transactions. These practices erode fiscal capacity, distort competitive markets, undermine economic transformation, and weaken state legitimacy. The problem is particularly acute in settings where customs capacity is uneven, incentives for informal payments are entrenched, and information asymmetries between customs officials and importers are large. In such contexts, the identification, measurement, and monitoring of trade fraud become essential components of evidence-based revenue administration and governance reform.

While numerous methods have been deployed to detect potential undervaluation (including transaction-level anomaly detection, price reference databases, and mirror-trade comparisons), each suffers from known limitations. Price databases struggle with heterogeneity in product quality and documentation accuracy; transaction-level investigations are resource-intensive and often impractical for high-volume ports; and mirrored trade statistics can mask discrepancies arising from reporting differences, classification issues, and timing mismatches. Recent advances in trade data harmonisation and the availability of highly disaggregated trade-unit-value datasets now provide an opportunity to revisit these methodological challenges.

This paper contributes to this growing literature by developing and applying a Trade Fraud Risk Index (TFRI), constructed from the distributional characteristics of cost, insurance, and freight (CIF)- free on board (FOB) trade unit value ratios derived from CEPII's Trade Unit Values (TUV) database. Rather than identifying fraud through anomalies in individual transactions, our approach examines systematic patterns in the distribution of unit value differences between importers' (CIF) and exporters' (FOB) data. The empirical regularities uncovered, namely, the clustering of countries into Laplace-, lognormal-, and exponential-type distributions, provide a novel basis for quantifying the relative risk of trade fraud across countries, over time, and across industries.

The TFRI is designed to serve as a parsimonious but powerful diagnostic tool. Its construction relies on two components that capture distinct distributional regimes associated with different levels of corruption risk and institutional quality. High-income, low-corruption economies tend to exhibit

Laplace-like CIF-FOB distributions, characterised by tight concentration around the expected insurance-and-transport cost margin. By contrast, low-income and high-corruption contexts tend to exhibit exponential-type distributions, where large shares of CIF-FOB ratios fall substantially below unity, a pattern strongly suggestive of widespread undervaluation. The resulting index has broad geographical and temporal coverage, is easy to update, and produces comparable measures of trade fraud risk for more than 200 countries from 2000-2019.

Although the construction of the TFRI is quantitative, the interpretation of its results requires careful consideration of institutional, behavioural, and operational dynamics within customs systems. For this reason, a significant contribution of the present paper is the integration of a qualitative fieldwork component conducted at the Port of Mombasa in November 2024. The Port of Mombasa is the principal gateway for Kenya's international trade and the largest container port in East Africa. It represents a high-volume, high-stakes environment in which customs valuation practices, enforcement mechanisms, and the behaviours of state and non-state actors interact to determine the effectiveness of trade regulation.

The field study involved semi-structured interviews with clearing agents, container freight station personnel, truck drivers, and other port workers, as well as direct observation of inspection facilities, document-handling processes, and cargo-flow procedures. These qualitative insights illuminate the mechanisms through which undervaluation and misreporting occur, the incentives faced by traders and customs officials, and how procedural discretion and institutional fragmentation create opportunities for collusion, facilitation payments, and avoidance of formal inspection triggers. The qualitative results also offer a valuable interpretive lens for understanding the sector-specific value gaps observed in the quantitative data, particularly in high-risk industries such as textiles, ceramics, and refined petroleum products.

Kenya offers an especially relevant case for the joint methodological approach employed in this study. Over the past two decades, Kenya has implemented substantial reforms in customs administration, including digitalisation of the declaration process, expansion of non-intrusive inspection technologies, adoption of risk-management protocols, and alignment with international standards under the East African Community (EAC) Customs Union. Kenya also has a longer history of governance and anti-corruption reforms than many of its regional counterparts, including being the first signatory worldwide to ratify the United Nations Convention Against Corruption (UNCAC). Despite these efforts, Kenya's performance on global corruption indexes has improved only modestly, and anecdotal evidence suggests that illicit behaviours remain resilient within parts of the customs system.

The contrast between Kenya's slow institutional progress and the more substantial improvements observed in its TFRI performance raises important questions about the relationship between general corruption indicators and specific forms of trade fraud. Indeed, the index reveals that Kenya's CIF-FOB distributions have shifted markedly toward the Laplace regime between 2005 and 2019, suggesting a substantive decline in the frequency of severe undervaluation. The estimated CIF-FOB trade gap and associated tariff revenue losses also decline substantially during this period, from approximately 31% to 7% of assessed FOB values. The qualitative field evidence, however, confirms the persistence of pockets of misreporting, including bribery to avert inspection flags, collusive misclassification schemes, and systematic undervaluation facilitated by information asymmetries between importers and customs officials.

By triangulating quantitative patterns with qualitative observations, the paper demonstrates that improvements in aggregate trade fraud indicators can coexist with enduring vulnerabilities at the operational level. The findings highlight the importance of considering institutional configurations, incentives for corruption, and the political economy of customs enforcement when interpreting statistical patterns in trade data. They also underscore the need for sector-specific analysis, as aggregate improvements may mask persistent risks in industries where tariff differentials are high, goods are easily misclassified, or inspection processes are particularly susceptible to discretionary interference.

The contribution of this paper is therefore threefold. First, it introduces a new Trade Fraud Risk Index grounded in distributional properties of CIF-FOB ratios, offering a widely applicable tool for identifying and ranking trade fraud risk internationally. Second, it extends existing approaches to value-gap estimation by incorporating trade volumes and WTO tariff structures to quantify potential revenue losses at a high level of product disaggregation. Third, it enriches the empirical analysis with granular qualitative evidence from a major African port, offering a rare view into the behavioural and institutional mechanisms underpinning observed patterns in trade data.

Taken together, this integrated methodology advances current understanding of trade fraud dynamics by bridging the gap between macro-level data analysis and micro-level institutional practice. The Kenyan case demonstrates that while quantitative indicators can capture broad improvements in trade integrity, qualitative insights are indispensable for identifying where fraud persists, how it is operationalised, and what types of policy interventions may be most effective. The approach thus provides a template for future research and for policymakers seeking to design targeted, evidence-based strategies to reduce trade fraud and strengthen customs revenue mobilisation.

The remainder of the paper is organized as follows. Section 2 describes the data used in the analysis. Section 3 outlines the empirical methodology. Section 4 presents the results, while Section 5 discusses the findings and concludes the paper.

2 Data

CEPII's Trade Unit Values (TUV) database

CEPII's trade unit values (TUV) are measured in USD/ton at the HS (harmonised system) 6-digit national industry level, available either as reported by the exporter (FOB, without transport costs) or as reported by the importer (CIF).[1] The trade unit values are used for the CIF/FOB ratio forming the basis for the Trade Fraud Risk Index (TFRI) and, when combined with trade volumes, assessed values of CIF/FOB differences or value gaps. The trade unit values are aggregated to the 4-digit level as the HS 4-digit level follows the convention in the economic complexity literature and, most importantly, because the results have been demonstrated to be more robust at the HS 4-digit level compared to the HS 6-digit level, which is also in agreement with Farhad et al. (2018).

According to Berthou and Emlinger (2010), trade unit values are commonly used as proxies for trade prices in empirical research in international economics. Existing datasets providing international trade unit values for many countries typically suffer from several statistical biases, due to the aggregation of unit values and the harmonization of quantity information. These biases reduce the

[1] CEPII TUV, see: http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=2

reliability of unit values as a proxy for trade prices. The TUV data from CEPII have been developed to circumvent these statistical issues. Bilateral trade unit values are computed at a very high level of disaggregation before aggregation into HS 6-digit industry level to allow for cross-country comparability. The processing strategy improves the differentiation of trade prices within product categories, as compared to existing worldwide datasets. A simple econometric analysis shows that unit values in the database are well explained by economic aggregates.

CEPII's BACI database

CEPII's BACI database contains trade values and volumes, where the UN COMTRADE data are cleaned by a method of harmonisation (Gaulier and Zignago, 2010). The data include the value of trade flows in current US dollars (USD), and the volume of trade flows in tons (MT), identified by the exporter, importer, and product category from the year 1995 to 2021. While the BACI trade volumes are multiplied by the CIF and FOB trade unit values to generate the CIF and FOB trade values used for assessing the values of the CIF-FOB differences, the BACI trade values are used as a control of the assessed CIF and FOB trade values. Like the trade unit values, the trade volumes are aggregated at HS 4-digit level for the same reasons as stated above.

WTO's tariff-download facility

WTO's tariff download facility contains data on Most- Favoured-Nation tariffs (MFN), Bound tariffs (BND) and Effectively Applied tariffs (AHS), as well as preferential tariffs, measured as either weighted/simple averages and minimum/maximum tariffs, at up to HS 6-digit level for over 170 countries. The WTO tariffs are aggregated at the HS 4-digit level to correspond to the trade unit values and trade volumes.

Qualitative data collected at Mombasa port

To better examine the mechanisms behind quantitative patterns, an exploratory field study was conducted at the Port of Mombasa in late 2024. The research team visited Kenya's largest port from November 19-28, 2024, meeting with a range of stakeholders including customs clearing agents, container freight station (CFS) staff, truck drivers, and others. In total, the field team toured three CFS facilities and the main port entry, and held semi-structured interviews with four clearing agents, multiple CFS employees, ten truck drivers, and other port workers. This qualitative inquiry offers ground-level insight into Kenya's import process and how misreporting practices lead to revenue loss, complementing the Trade Fraud Risk Index (TFRI) results with on-the-ground observations.

3 Quantitative Methodology

CIF/FOB ratios

The distributions of CIF/FOB ratios are used to illustrate the frequency of CIF-FOB differences in a country's imports. The CIF/FOB ratios are calculated using CEPII's trade unit values and are assessed at HS 4 digit-level (up to around 1,230 industries) for up to 230 import and export countries over the period 2000-2019, totalling around 24 million observations:

$$CIF\ FOB\ ratio_{piet} = \frac{CIF\ TUV_{piet}}{FOB\ TUV_{piet}} \quad (1)$$

p = 1, …,~ 1,230, i = 1, ….,~ 230, e = 1, ….,~ 230, t = 2000, …., 2019

$CIF\ TUV_{piet}$: *CIF import unit trade value (USD/MT) for product p imported to reporting country i from exporting partner country e, at time t.*

$FOB\ TUV_{piet}$: *FOB export unit trade value (USD/MT) for product p exported to importing partner country i from exporting reporting country e, at time t.*

The CIF/FOB ratio is often used by trade economists to proxy trade costs, particularly transportation costs. Examples include UNCTAD's and OECD's databases on transport and insurance costs derived from CIF/FOB ratios, see UNCTAD (2022), and OECD (2022). In a perfect world, the CIF/FOB ratios should reflect trade costs including transport and insurance costs.

However, it is also clear that the CIF/FOB ratio captures many other factors such as potential trade fraud, different CIF-FOB definitions, different valuation methods, flawed trade value assessments, time lags, etc., see, for example, Chasomeris (2009) and Kee and Nicita (2022). Hummels and Lugovsky (2006) show from a sample of 17,790 country pairs in 1997 that only around 50% of the total bilateral trade flows have an order of magnitude that could be considered reasonable. Consequently, as in this study, the CIF/FOB ratios have also been used to detect customs fraud in the form of under- and/or overvaluation of imports and exports.

According to Grigoriou (2019), global studies have focused on the correlation between CIF/FOB ratios and macroeconomic variables related to governance and public sector integrity indicators, such as corruption level, tariff level and the complexity of its structure; national studies have focused on the "evasion gap" and the tax rates, where higher tariff and tax rates are associated with higher undervaluation of imports. Finally, studies such as this one have focused on identifying fraud channels and possible revenue losses; see, for example, Canten (2015) and Chalendard et al. (2016 and 2021).

Trade Fraud Risk Index (TFRI)

The distributions of CIF/FOB ratios are useful and illustrative for assessing the risk of trade fraud for individual countries but are rather cumbersome for ranking countries and examining individual countries over time. Therefore, an index of trade fraud risk is proposed to replace the use of actual distributions with selected characteristics of the distributions.

The index includes two components. Component 1 aims to capture and rank low-income/high-corruption countries, whose CIF/FOB ratios can be approximated by an exponential distribution and where the CIF/FOB ratios should be somewhere below a threshold value of 1.0, see **Figure 4.2** Component 1 is defined as the percentage of CIF/FOB ratios below this threshold divided by the percentage of CIF/FOB ratios above the threshold at the HS 4-digit level:

$$Component\ 1_{it} = \frac{\sum_{p=1}^{\sim 1,230} \sum_{e=1}^{\sim 230} CIF\ FOB\ ratio_{piet} < threshold_{c1}}{\sum_{p=1}^{\sim 1,230} \sum_{e=1}^{\sim 230} CIF\ FOB\ ratio_{piet} \geq threshold_{c1}} \quad (2)$$

p = 1, …,~ 1,230, i = 1, ….,~ 230, e = 1, ….,~ 230, t = 2000, …. , 2019

Component 2 targets high-income/low-corruption countries, whose CIF/FOB ratios can be approximated by a Laplace distribution and where the CIF/FOB ratios should be somewhere around a threshold value of 1.0, see **Figure 4.1**. In these countries, under- and/or overvaluation of imports or exports is relatively low, and most of the differences in the CIF/FOB ratios can be attributed to insurance and transport costs.[2] Component 2 is defined as the percentage of CIF/FOB ratios between thresholds below and above one divided by the percentage of CIF/FOB ratios between these thresholds for all countries per year at HS 4-digit level:

$$Component\ 2_{it} = \frac{\sum_{p=1}^{\sim 1,230} \sum_{e=1}^{\sim 230} threshold_{c2\ low} < CIF\ FOB\ ratio_{piet} < threshold_{c2\ high}}{\sum_{p=1}^{\sim 1,230} \sum_{i=1}^{\sim 230} \sum_{e=1}^{\sim 230} threshold_{c2\ low} < CIF\ FOB\ ratio_{t} < threshold_{c2\ high}} \quad (3)$$

p = 1, …,~ 1,230 (HS4), i = 1, ….,~ 230, e = 1, ….,~ 230, t = 2000, …. , 2019

The TFRI is composed of components 1 and 2 in a standardized form to ensure both contribute evenly. The TFRI ranges from plus to minus with high positive values for low-income/high-corruption countries and high negative values for high-income/low-corruption countries.

As an index that focuses narrowly on fraud in the form of undervaluation of imports, the TFRI appears to occupy a small niche. Apart from corruption indexes with broad coverage, such as, for example, Transparency International's Corruption Perception Index (and all the indexes included)[3] and PWCs Global Economic Crime and Fraud Survey[4], there seems to be relatively few indexes like the TFRI with a narrow focus and broad coverage over time and countries. According to Grigoriou (2019), most studies with a similar focus on CIF/FOB ratios focus on individual countries and/or industries and do not have coverage over time and countries. Others use econometric modelling to detect undervaluation of imports, see for example Kee and Nicita (2022), but none seem to have large country coverage over a significant period such as the TFRI.

CIF-FOB differences (trade gaps)

The CIF/FOB ratios indicate the frequency of CIF and FOB differences. To assess the value of CIF-FOB differences, CIF and FOB trade unit values are multiplied by CEPII's BACI trade volumes to assess the CIF and FOB trade values. As BACI trade volumes are the same for CIF and FOB trade values, potential fraud with volumes will not be captured. The CIF and FOB values are assessed at HS 4 digit-level (up to 1,230 industries) for up to 230 import countries, up to 230 export countries over the period 2000-2019, totalling around 24 million observations:

[2] In practice, it is however impossible to reduce the differences between CIF and FOB values to just insurance and transport costs. Numerous other factors will contribute including various definitions of CIF and FOB values used in different countries, see for example IMF (2020), as well as measurement and assessment errors and failures, see for example OECD (2018).

[3] Transparency International CPI 2022: https://www.transparency.org/en/cpi/2023?gad_source=1&gclid=CjwKCAiA_aGuBhACEiwAly57MTB4kW_kLfJHLFT61o0MgZkAcF7pdp_bS8Rgxs3fEx9CmyxfPlndPBoCp5gQAvD_BwE .

[4] PWC Global Economic Crime and Fraud Survey: https://www.pwc.com/gx/en/services/forensics/economic-crime-survey.html

$$CIF\ import\ value_{piet} = Q_{piet} \times CIF\ TUV_{piet} \tag{4}$$

$$CIF\ import\ value_{it} = \sum_{e=1}^{\sim 230} \sum_{p=1}^{\sim 1{,}230} CIF\ import\ value_{piet} \tag{5}$$

p = 1, …,~ 1,230, i = 1, ….,~ 230, e = 1, ….,~ 230, t = 2000, …. , 2019

Q_{piet}: *Volume of product p imported to reporting importing country i from exporting partner country e, at time t.*

$CIF\ import\ value_{piet}$: *CIF import trade value (USD) for product p imported to reporting country i from exporting partner country e, at time t.*

$CIF\ import\ value_{it}$: *CIF import trade value (USD) imported to reporting country i from exporting partner country e, at time t.*

$$FOB\ export\ value_{piet} = Q_{piet} \times FOB\ TUV_{piet} \tag{6}$$

$$FOB\ export\ value_{it} = \sum_{e=1}^{\sim 230} \sum_{p=1}^{\sim 1{,}230} FOB\ export\ value_{piet} \tag{7}$$

p = 1, …,~ 1,230, i = 1, ….,~ 230, e = 1, ….,~ 230, t = 2000, …. , 2019

Q_{piet}: *Volume of product p exported to partner importing country i from exporting reporting country e, at time t.*

$FOB\ export\ value_{piet}$: *FOB export trade value (USD) for product p exported to partner country i from exporting reporting country e, at time t.*

$FOB\ export\ value_{it}$: *FOB export trade value (USD) exported to partner country i from exporting reporting country e, at time t.*

CIF-FOB tariff revenue

To assess potential customs revenue loss, tariff rates are multiplied by assessed CIF and FOB values. The difference between CIF and FOB tariff revenue is the potential customs revenue loss. As a starting point, WTO simple averages of MFN tariff rates at the HS 4-digit level are applied. The CIF and FOB tariff revenues are assessed at HS 4 digit-level (up to around 1,230 industries) for up to 230 import countries, up to 230 export countries over the period 2000-2019, totalling around 24 million observations:

$$CIF\ tariff\ revenue_{piet} = CIF\ import\ value_{piet} \times Tariff_{piet} \tag{8}$$

$$CIF\ tariff\ revenue_{it} = \sum_{e}^{\sim 230} \sum_{p}^{\sim 1,230} CIF\ import\ value_{piet} \times Tariff_{piet} \tag{9}$$

p = 1, …,~ 1,230, i = 1, ….,~ 230, e = 1, ….,~ 230, t = 2000, …. , 2019

$Tariff_{piet}$	*Tariff (WTO MFN Simple average) level applicable in the importing country i for product p for the product classification registered in the importing reporting country i at time t.*
$CIF\ tariff\ revenue_{piet}$:	*Tariff revenue (USD) for product p for the product classification and unit value registered by the importing reporting country i at time t.*
$CIF\ tariff\ revenue_{it}$:	*Tariff revenue (USD) for importing country i for imported products with the classification and unit values as registered by the importing reporting country i at time t.*

$$FOB\ tariff\ revenue_{piet} = FOB\ import\ value_{piet} \times Tariff_{piet} \tag{10}$$

$$FOB\ tariff\ revenue_{it} = \sum_{e}^{\sim 230} \sum_{p}^{\sim 1,230} FOB\ import\ value_{piet} \times Tariff_{piet} \tag{11}$$

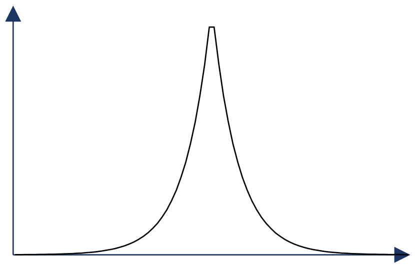
p = 1, …,~ 5,200, i = 1, ….,~ 230, e = 1, ….,~ 230, t = 2000, …. , 2019

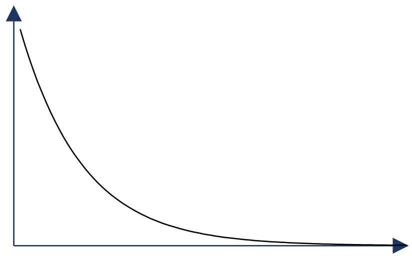
$Tariff_{piet}$	*Tariff (WTO MFN Simple average) level applicable in the importing country i for product p for the product classification registered by exporting reporting country e, at time t.*
$CIF\ tariff\ revenue_{piet}$:	*Tariff revenue (USD) for product p if the product had the classification and unit value as registered by exporting reporting country e, at time t.*
$CIF\ tariff\ revenue_{it}$:	*Tariff revenue (USD) for importing country i for imported products with the classification and unit values as registered by the exporting reporting country e, at time t.*

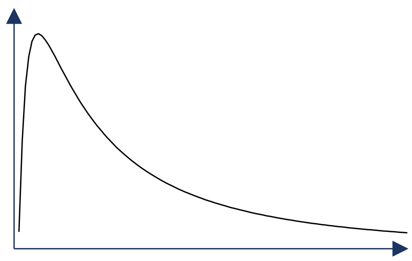
4 Results

4.1 The frequency of CIF/FOB ratios

CIF and FOB trade unit values are first examined to assess their suitability as potential building blocks for the construction of a trade fraud risk index. It was only during this examination that the distribution patterns of the CIF/FOB ratios became apparent and were later selected as the most suited building blocks for the construction of the index.







The distribution patterns of CIF/FOB ratios can be classified into three types, which are categorized as either a Laplace, an exponential, or a lognormal distribution.

The Laplace distribution fits countries with a balanced concentration of CIF/FOB ratios around a mean value. This mean was originally set at 1.1, assuming an average insurance and transport cost of roughly 10%, as they normally vary from a few percentages to up to 20%, see for example Grigoriou et al. (2019), and UNCTAD (2022). However, 'Laplace countries' typically have a mean CIF/FOB ratio lower than 1.1, indicating transport and insurance costs of less than 10%, see **Figure 4.1**.

While many 'Laplace countries' can be categorised as high-income and low-corruption countries, this is not always the case. Countries such as Romania and Turkey, which ranked 70/180 and 91/180 on Transparency International's Corruption Perception Index (CPI) in 2019, are also characterised as 'Laplace countries'.

The exponential distribution fits countries with a significant imbalance in CIF/FOB ratios, where most CIF values are lower than the corresponding FOB value, i.e. a high degree of undervaluation of imported goods and potential loss of customs revenue.

While the 'Laplace countries' consist of somewhat mixed levels of income and corruption, albeit in the positive range, the 'exponential countries' consist almost entirely of low- and lower-middle-income and high-corruption countries, including Angola, Sierra Leone, Mauritania, Nigeria, Sudan, Congo, Comoros and Myanmar, see **Figure 4.2.**

Finally, the log-normal distribution fits countries that seem to be in a transition between the exponential and Laplace-distributed CIF/FOB ratios. Examples include Botswana, Cote d'Ivoire, Ethiopia, Kenya, Malawi, Namibia, Philippines, and Brunei Darussalam, see **Figure 4.3**. These countries range from low-income to lower/upper middle-income countries with CPI country ranking from 35/180 to 137/180 in 2019, corresponding to medium to low corruption levels according to Transparency International.

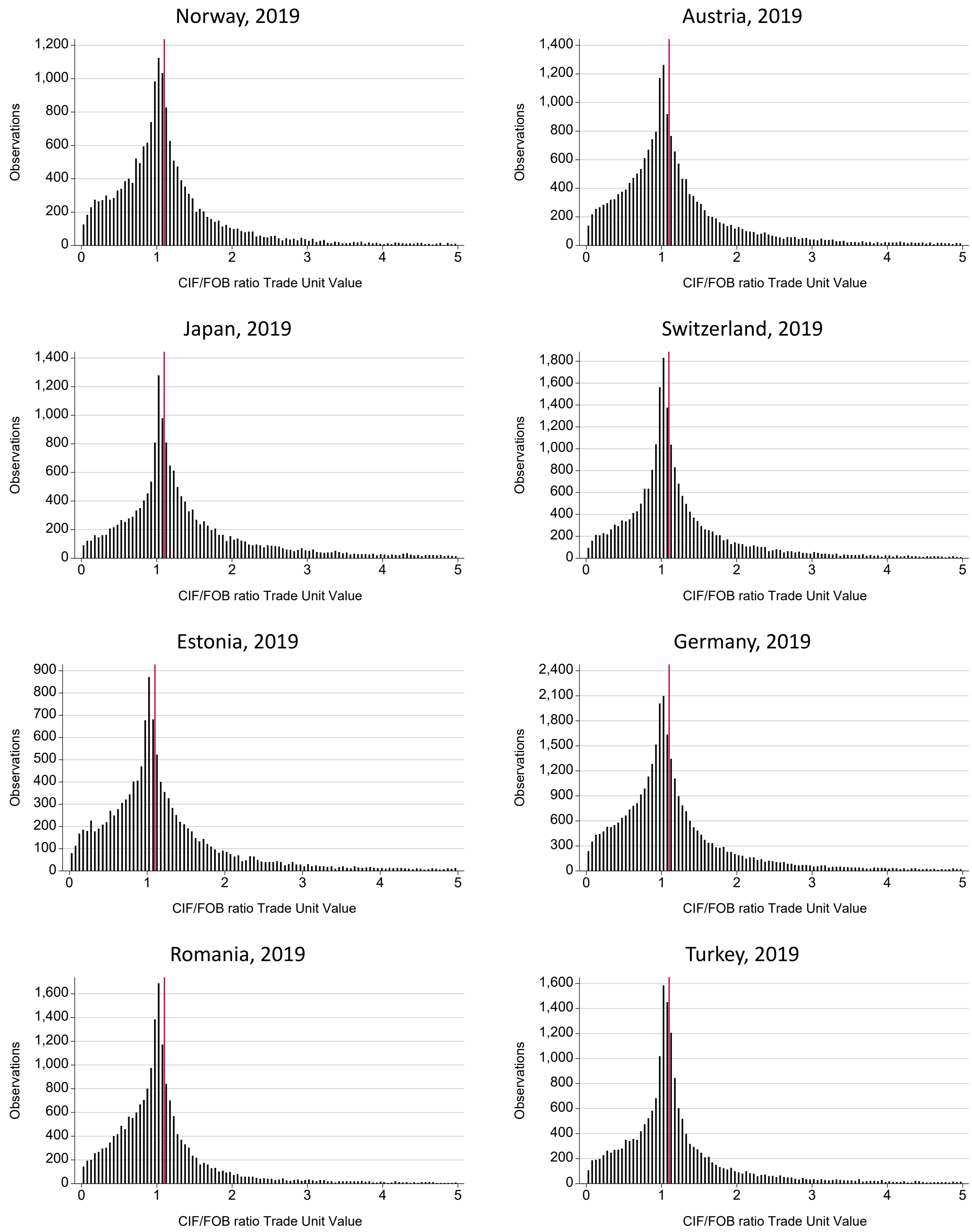


Figure 4.1: CIF/FOB ratio - HS 4-digit level – "Laplace countries"

Note: Red line at CIF/FOB ratio of 1.1 marks a potential 10% insurance and transport costs.

Source: Authors' calculations based on CEPII, Trade Unit Values.

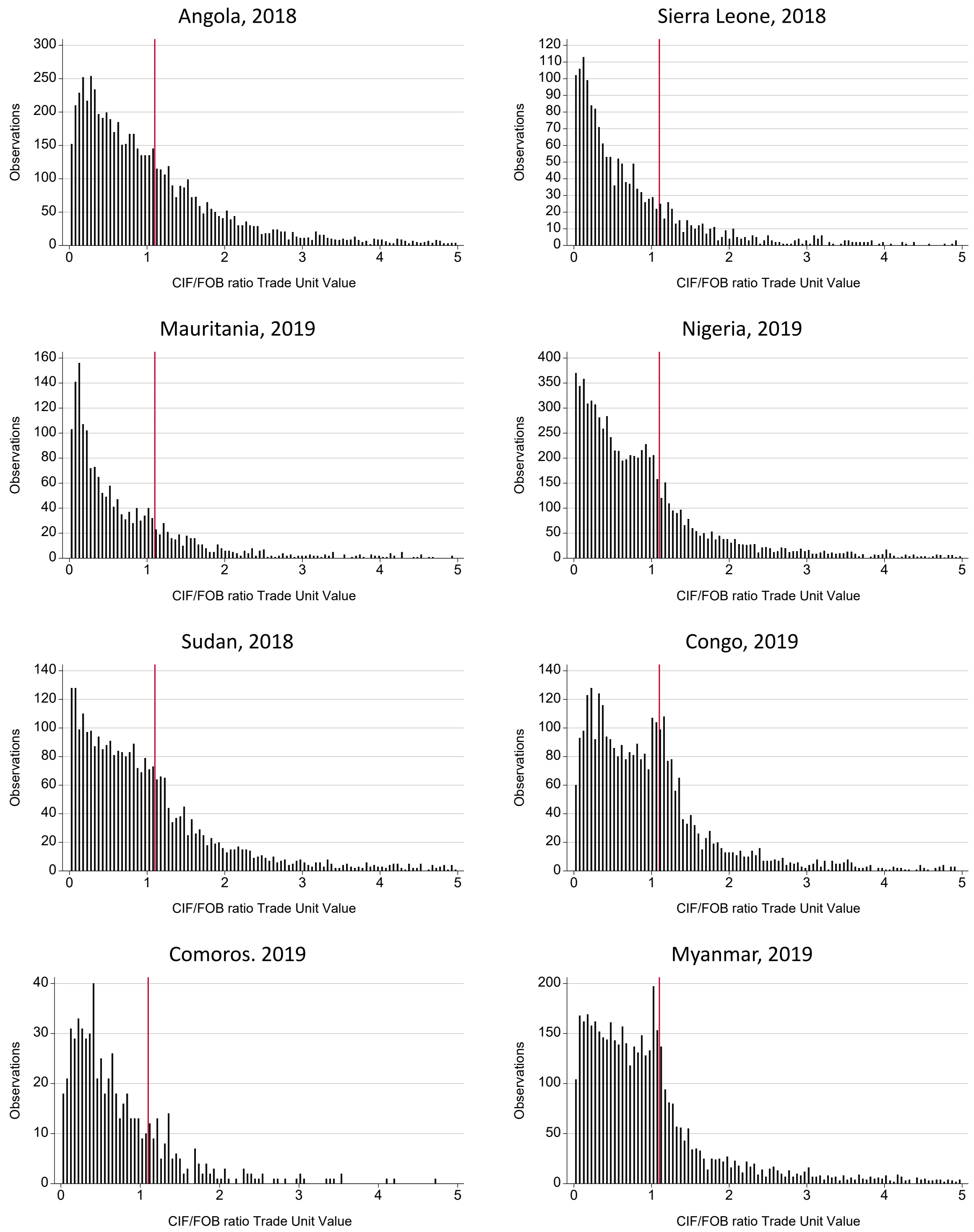


Figure 4.2: CIF/FOB ratios - HS 4-digit level – "exponential countries"

Note: Red line at CIF/FOB ratio of 1.1 marks a potential 10% insurance and transport costs.

Source: Authors' calculations based on CEPII, Trade Unit Values.

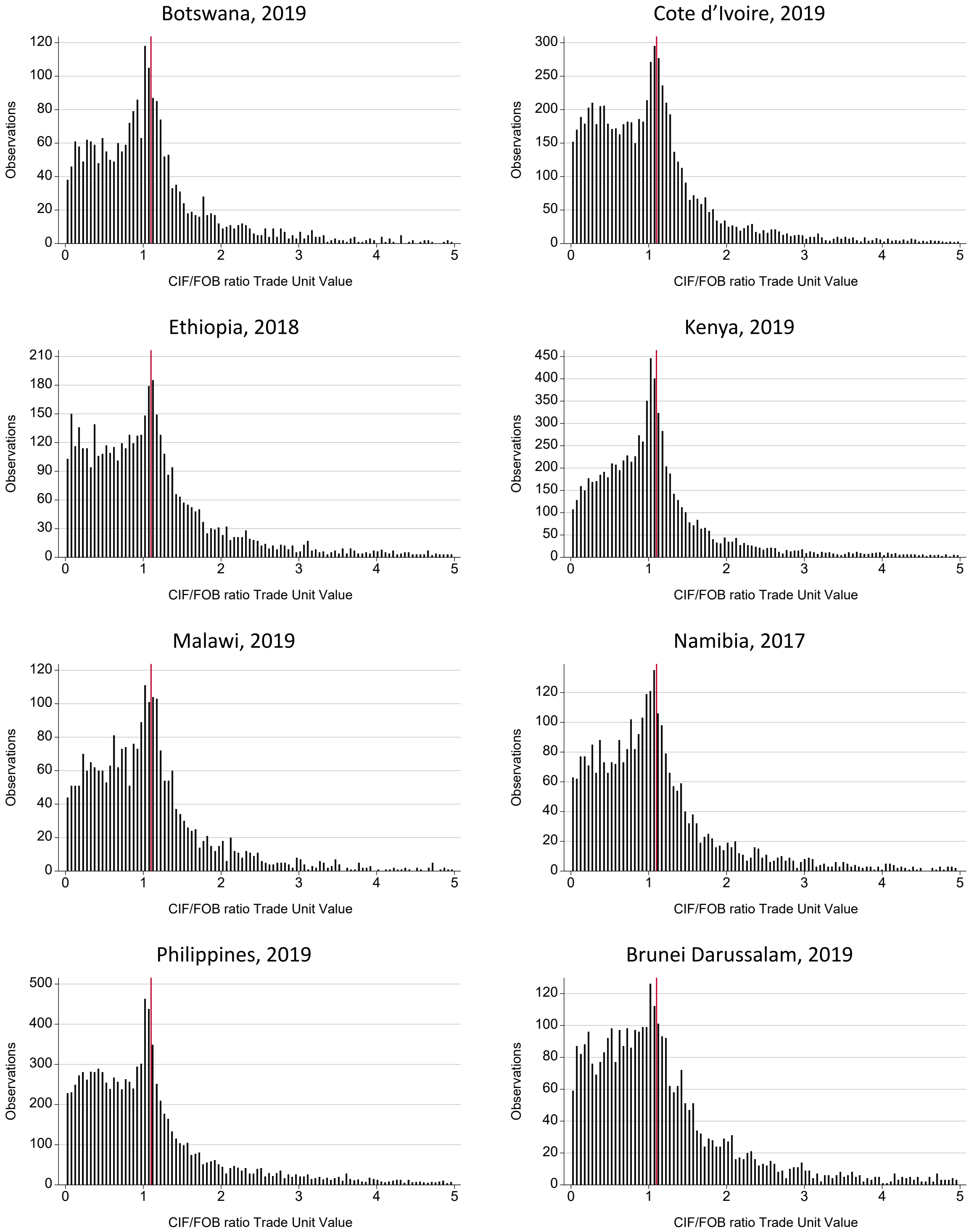


Figure 4.3: CIF/FOB ratios - HS 4-digit level – "log-normal countries"

Note: Red line at CIF/FOB ratio of 1.1 marks a potential 10% insurance and transport costs.

Source: Authors' calculations based on CEPII, Trade Unit Values.

4.2 A Trade Fraud Risk Index (TFRI)

The distributions of CIF/FOB ratios are useful and illustrative for assessing the risk of trade fraud for individual countries but are rather cumbersome for ranking countries and examining individual countries over time. Therefore, an index of trade fraud risk is proposed to replace the use of actual distributions with selected characteristics of these distributions.

The index is proposed to include two components based on the observed characteristics of the CIF/FOB ratios, where low-income/high-corruption countries can be approximated by exponential distributions with a high concentration of observations below one, and high-income/low-corruption countries can be approximated by Laplace distributions with a high concentration of observations around the mean corresponding to the insurance and transport costs.

On this basis, the first component is constructed to capture the exponential distribution and measures the percentage of CIF/FOB ratios below one, **see Figure 4.2**. A robustness check examining the sensitivity of the TFRI country ranking to different component values shows relatively constant country rankings among high-risk countries when component 1 is between 0.3 and 0.7, see Appendix A. On this basis, the threshold value for component 1 is set to 0.5, see **Figure 4.4**.

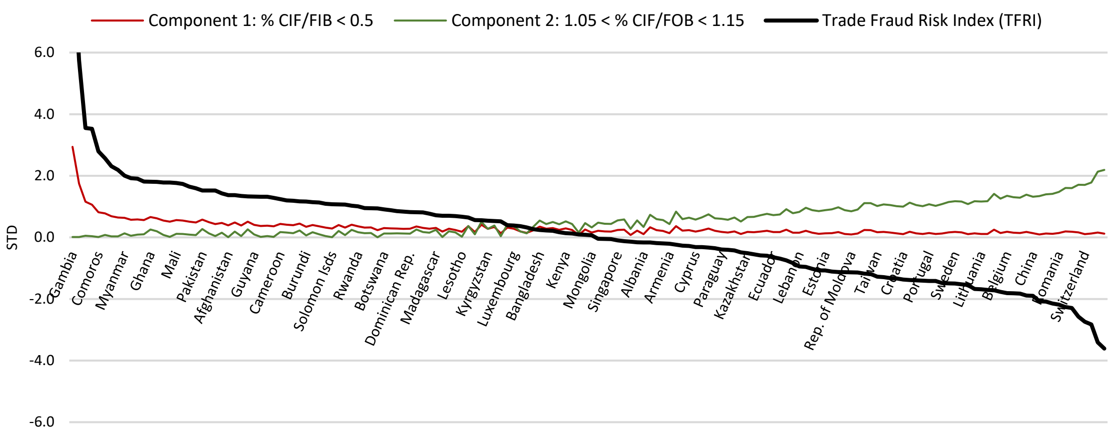


Figure 4.4: A Trade Fraud Risk Index (TFRI) based on CIF/FOB ratios, average 2015-2019

Source: Authors based on CEPII, Trade Unit Values.

While component 1 captures and ranks low-income/high-corruption countries, it is less suited for capturing high-income/low-corruption countries; see the flattening of the red line in **Figure 4.4**. Component 2 aims to address this gap and targets high-income/low-corruption countries, whose CIF/FOB ratios can be approximated by a Laplace distribution and where the CIF/FOB ratios should be somewhere around a threshold value corresponding to the insurance and transport costs.

The robustness check shows that TFRI country ranking to different component values is relatively constant among high-risk countries when component 2 is between 0.9 and 1.2, see Appendix A. On this basis, the threshold values for component 2 are set to 1.05 and 1.15. The trade fraud risk index is composed of the two components in a standardized form to ensure both components contribute evenly. The index ranges from plus to minus, with high positive values for low-income/high-corruption countries and high negative values for high-income/low-corruption countries, see **Figure 4.4**.

As the TFRI is targeting trade fraud and not corruption in a broad sense, it is not expected to be significantly correlated with other corruption indices such as African Development Bank (AfDB) Country Policy and Institutional Assessment, the Bertelsmann Stiftung Sustainable Governance Indicators, or the Economist Intelligence Unit Country Risk Service, all included in Transparency International's CPI (CPI 2022).

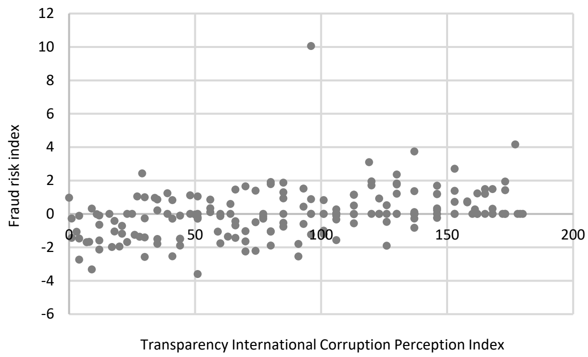


Figure 4.5: Trade Fraud risk index and Transparency International's CPI, 2019
Source: Authors' calculations based on CEPII, Trade Unit Values.

In 2019, the correlation between the TFRI and the CPI was 46%, see **Figure 4.5.** According to the CPI, the top five most corrupt countries were Somalia, South Sudan, Syria, Yemen and Venezuela. In the TFRI, only Yemen is also included among the top five countries with the highest trade fraud risk. Other countries included were Gambia, Belize, Mauritania and Sierra Leone, see **Table 4.1**, clearly demonstrating that the two indices, as expected and intended, are only partly complementary and each providing new additional information.

Table 4.1: Top10 countries with the highest trade fraud risk, TRFI, 2000-2019

Top10	2000	2005	2010	2015	2019
1	Gambia	Gambia	Gambia	Gambia	Gambia
2	Mauritania	Mauritania	Mauritania	Belize	Belize
3	Nigeria	Guinea-Bissau	Nigeria	Mauritania	Yemen
4	Libya	Guinea	Libya	Myanmar	Mauritania
5	Cambodia	Nigeria	Myanmar	Comoros	Sierra Leone
6	Myanmar	Libya	Dominican Rep.	Guinea	Bahamas
7	Sierra Leone	Togo	Comoros	Benin	Comoros
8	Togo	Myanmar	Cambodia	Nigeria	Afghanistan
9	Dominican Rep.	Cambodia	Benin	Burkina Faso	Samoa
10	Bahamas	Zimbabwe	Togo	Niger	Ghana

Source: Authors' calculations based on CEPII, Trade Unit Values.

The TFRI identifies Gambia as the country with the highest fraud risk, not only in 2019, but also in 2015, 2010, 2005 and 2000, i.e., consistently over 19 years. This might seem odd considering the CPI ranks Gambia as a country with a medium corruption level (96 out of 180 countries in 2019). Even more so considering the Bahamas was identified as a top-10 high-risk fraud country in 2000 and 2019 by the TFRI, while ranked as a low corruption country (29 out of 180 countries in 2019) by the CPI in 2019. The same kind of differences apply to countries such as Ghana, Suriname, and Burkina Faso, where the TFRI assesses a high fraud risk, while the CPI assesses a low to medium corruption level.

As such, the TFRI is identifying something additional and different from the traditional corruption indices. By targeting a specific activity such as undervaluation of imports, as opposed to the general level of corruption, it provides actionable results that may be useful to private sector participants contemplating or engaged in business activities requiring imports such as Cut-Make-Trim (CMT) or Cut-Make-Pack (CMP) models, or to customs authorities and ministries of finance seeking to monitor and evaluate the effectiveness of risk and other management programmes.

Global Financial Integrity

Global Financial Integrity (GFI)[5] assesses trade gaps by comparing CIF import values with FOB export values at product level. GFI believes the majority of its identified trade gaps are indicative of trade mis-invoicing activity and identifies that trade mis-invoicing is one of the largest components of measurable illicit financial flows (GFI, 2021).[6] By adding trade volumes, the TFRI can also be used to assess trade gaps in terms of the value of CIF-FOB differences, which in turn makes GFI's assessments suitable for verification and comparison with the authors' trade value assessments.

However, it is crucial to highlight that the GFI's evaluations diverge from this paper on several fronts. GFI adheres to the methodology of Miao and Fortanier (2016) by limiting the UN COMTRADE data to solely "reliable" observations, an approach not adopted in the utilization of CEPII trade unit values in this study. More specifically, GFI incorporates into the statistical model only those matched trades meeting the criteria that (a) the associated trade volumes show a difference of less than 5%, and (b) the ratio of the import (CIF) price per unit to the corresponding export (FOB) price falls between one and two (GFI, 2021). As the aim of this study is to assess potential fraud, it does not seem appropriate to restrict the trade unit values as this could distort the objective.

Additionally, GFI employs a gravity-type model, akin to CEPII, to convert CIF values to FOB values, accounting for insurance and transport costs, while incorporating supplementary explanatory factors. However, given that adjusting for insurance and transport costs may inadvertently address other factors, such as those linked to trade fraud, this study opts to retain insurance and transport costs in the data and utilizes CIF values. Furthermore, this paper diverges from GFI's approach by employing identical trade unit values and volumes for both importers and exporters, whereas GFI utilizes actual reported trade values from importing and exporting countries. Due to these differences as well as varying data quality, comparison of trade gaps between GFI and this paper differs substantially for some countries, while surprisingly similar for other countries, which is likely to emphasise the uncertainty of assessments using this framework, see **section 4.3** and **section 4.4**.

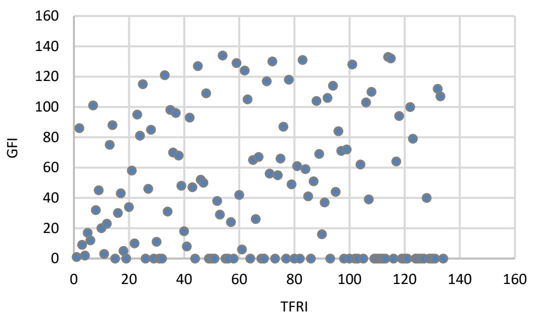


Figure 4.6: Trade Fraud risk index and GFI, 2018

Source: Authors' calculations based on CEPII, Trade Unit Values, and GFI 2021.

The GFI study also offers an opportunity to compare the frequency of CIF-FOB differences as given by the TFRI with the value of the CIF-FOB differences as given by the GFI. Pope et al. (2014) concluded that the frequency of undervaluation shows no correlation with the value of undervaluation. Comparing the top-10 countries with the highest frequencies and values, respectively, from 2009 to 2018, only 32 out of a total of 100 countries are identified, while 68 countries are not. Also, a scatter plot of the GFI and TFRI country ranking clearly shows many differences; see **Figure 4.6.**

However, some countries are characterized by both high frequency and high value in their CIF-FOB differences and among the most prominent are Gambia and the Bahamas, see below.

[5] Global Financial Integrity (GFI). See: https://gfintegrity.org/

[6] Global Financial Integrity (GFI). See: https://gfintegrity.org/report/trade-related-illicit-financial-flows-in-134-developing-countries-2009-2018/

Case Gambia

Gambia consistently emerges as the nation linked to the utmost risk of fraud according to both the GFI and the TFRI, not only in a singular year but throughout all the years encompassed by both studies. This implies that Gambia is prone to experiencing both a frequent occurrence and a substantial magnitude of differences between CIF and FOB values. Since 2009, the GFI has consistently appraised Gambia's value gap at an average of approximately 52% of its total bilateral trade, marking the highest percentage evaluated for any country.

Since 2000, the TFRI has similarly assessed that Gambia has consistently increased the percentage of CIF/FOB ratios below 0.5, indicating an increasing frequency of potential undervaluation of imports, while the percentage of CIF/FOB ratios between 1.05 and 1.15 is close to zero in all years, see **Figure 4.7**. The high percentage of CIF/FOB ratios below 0.5 and the low percentage between 1.0 and 1.2 is further illustrated by the distribution of CIF/FOB ratios in 2019, see **Figure 4.8**.

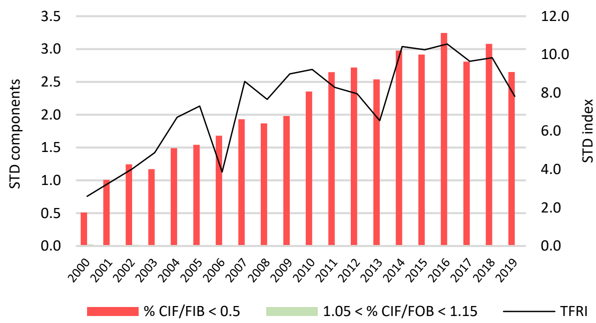


Figure 4.7: TFRI components and index value, Gambia, 2000-2019

Source: Authors' calculations based on CEPII, Trade Unit Values.

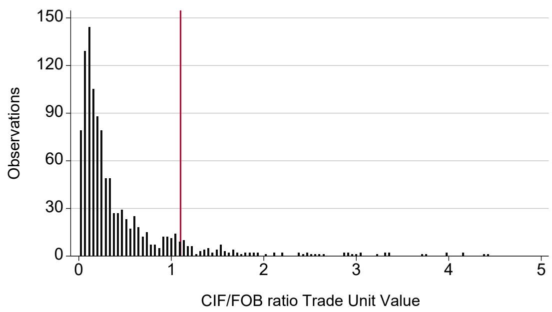


Figure 4.8: CIF/FOB ratios, Gambia, 2019

Source: Authors' calculations based on CEPII, Trade Unit Values.

As mentioned above, Transparency International's CPI ranks Gambia 96 out of 180 countries in 2019, indicating a relatively moderate level of corruption. This ranking has remained rather stable since 2012.[7] In Gambia, Banjul is a regional entry point, where products can be imported and exported without paying import duties. As a result, Gambia's re-exports account for over 80% of the country's total exports. Gambia's main export partners are Senegal, Guinea, the UK, China, Guinea-Bissau, Ghana, and India.[8] Of these, India and China are also rated by GFI as having the highest relative trade gaps with developing countries.[9]

Case Bahamas

The GFI and the TFRI have identified another country, Bahamas, as posing a significant risk of trade fraud, although their assessments are for different years within the 2009-2018 timeframe. From 2009 onward, the GFI has consistently evaluated the trade gap for Bahamas at an average of approximately 24%, comparing it to 134 developing countries and their respective trading partners. On the other hand, the TFRI suggests that the Bahamas demonstrated an improvement in trade fraud risk between 2000 and 2014, but this progress has regressed significantly since then, reverting to the same level as observed in 2000 by 2018. Since 2014, the percentage of CIF/FOB ratios below 0.5 has increased significantly, while the percentage of CIF/FOB ratios between 1.05 and 1.15 has

[7] Transparency International, see: https://www.transparency.org/en/cpi/2018/index/gmb
[8] Inter-Governmental Action Group against Money Laundering (GIABA), see: https://www.giaba.org/about-giaba/index.html
[9] Global Financial Integrity (GFI), see: https://gfintegrity.org/report/trade-related-illicit-financial-flows-in-134-developing-countries-2009-2018/

remained consistently low, see **Figure 4.9**. The high risk of trade fraud is further illustrated by the distribution of CIF/FOB ratios in 2018, see **Figure 4.10**.

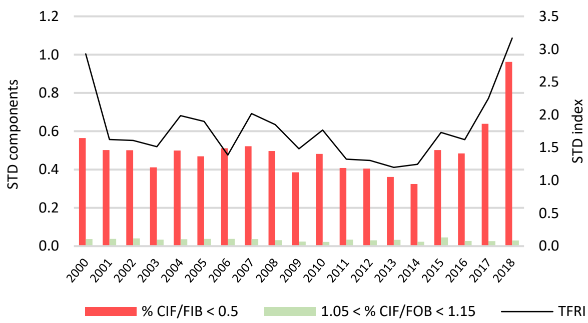


Figure 4.9: TFRI components and index value, Bahamas, 2000-2018

Source: Authors' calculations based on CEPII, Trade Unit Values.

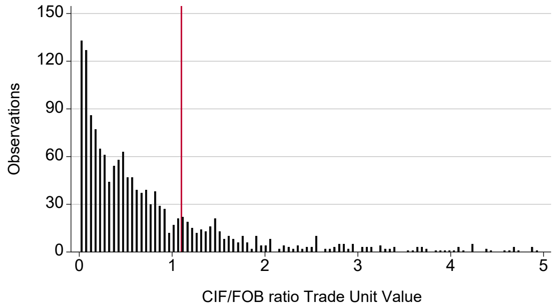


Figure 4.10: CIF/FOB ratios, Bahamas, 2018

Source: Authors' calculations based on CEPII, Trade Unit Values.

Compared to Transparency International's CPI, this is even more surprising than Gambia, as CPI ranked the Bahamas 29 out of 180 countries in 2019, indicating a relatively low level of corruption. This ranking has remained relatively stable since at least 2016.[10]

Top-10 countries with the lowest trade fraud risk

The Gambia and Bahamas cases show how the GFI and the TFRI provide complementary information compared to the Transparency International CPI and probably other similar corruption indices. However, over the period 2000-2019, while the TFRI identifies countries such as Germany, the United Kingdom, Switzerland, Japan, and France as top-10 countries with the lowest risk of trade fraud, it also identifies countries such as Turkey, Bulgaria, Czechia, and Romania, which are not normally considered to be top performers when it comes to non-fraudulent practices, see **Table 4.2**.

Table 4.2: Top-10 countries with the lowest trade fraud risk, TRFI, 2000-2019

Top-10	2000	2005	2010	2015	2019
1	Czechia	Lithuania	Japan	United Kingdom	Rep. of Korea
2	Finland	Turkey	Romania	Japan	United Kingdom
3	United Kingdom	Japan	United Kingdom	Romania	USA
4	Japan	United Kingdom	France	USA	Bulgaria
5	USA	USA	Spain	Spain	France
6	France	Spain	Turkey	Turkey	Spain
7	Spain	France	USA	France	Turkey
8	Switzerland	Switzerland	Switzerland	Switzerland	Switzerland
9	Italy	Germany	Germany	Germany	Germany
10	Germany	Italy	Italy	Italy	Italy

Source: Authors' calculations based on CEPII, Trade Unit Values.

Additionally, in 2019, CPI ranked Turkey 91 out of 180 countries, while Romania was ranked 70. Although these rankings are not among the lowest, they are clearly not associated with top performance in terms of non-corruption. However, when looking at Turkey and Romania's TFRI and CIF/FOB ratios, they show top performance in terms of low risk of trade fraud given in terms of undervaluation of imports, see **Figure 4.11**-**Figure 4.14** below. It follows that a medium to high level of corruption, as indicated by Transparency International's CPI, does not automatically imply a high

[10] Transparency International, see: https://www.transparency.org/en/cpi/2018/index/gmb

risk of trade fraud, as indicated by the TFRI. This is not the same as no trade fraud exist; it is just not in the form of CIF and FOB differences.

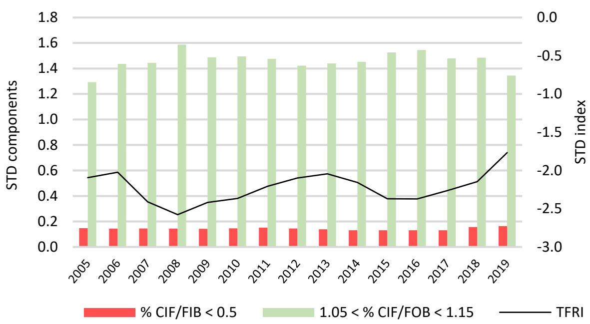


Figure 4.11: TFRI components and index value, Romania, 2000-2018

Source: Authors' calculations based on CEPII, Trade Unit Values.

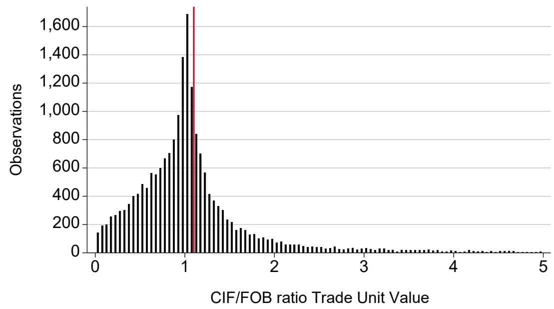


Figure 4.12: CIF/FOB ratios, Romania, 2019

Source: Authors' calculations based on CEPII, Trade Unit Values.

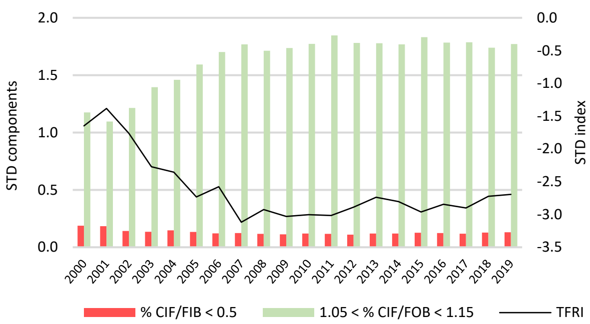


Figure 4.13: TFRI components and index value, Turkey, 2000-2018

Source: Authors' calculations based on CEPII, Trade Unit Values.

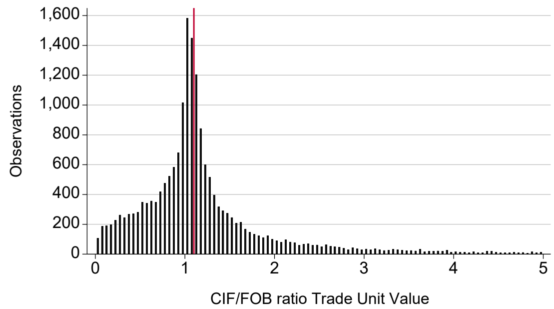


Figure 4.14: CIF/FOB ratios, Turkey, 2019

Source: Authors' calculations based on CEPII, Trade Unit Values.

4.3 The value of CIF-FOB differences (trade gaps)

The values of CIF-FOB differences are assessed simply by multiplying the trade unit values by the trade volumes. The trade volumes used are from the CEPII BACI database[11], which means that CIF and FOB volumes are identical and therefore potential volume fraud is not captured.

This shortcoming is also an advantage as the use of consistent trade volumes, in combination with unit trade values, as opposed to total trade values, is more effective in detecting undervaluation compared to various other forms of trade fraud. Thus, it is expected that our approach eliminates CIF-FOB variation arising from 1) misclassification, 2) misdeclarations of quantities, 3) double invoicing, 4) time lags, 5) disparities in the way reporting countries record data for transit, transshipment, or trade through third countries in general (Ferrantino and Wang, 2008; Barbieri et al., 2009), and other fraudulent activities. Additionally, the inclusion of insurance and transport ensures there is no potential bias or overcorrection introduced by a gravity model. The resulting CIF-FOB differences include insurance and transport costs that normally are expected to vary from a few percentages and up to 20%, see for example Grigoriou et al. (2019) and UNCTAD (2022).

[11] CEPII BACI, see: http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37

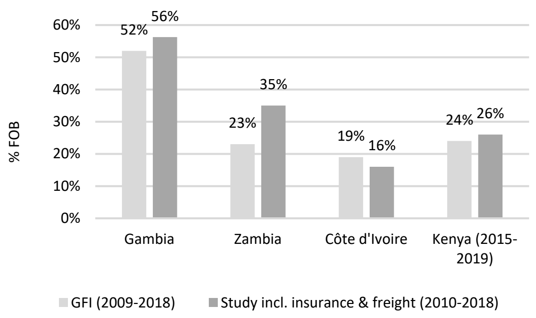


Figure 4.15: Trade gap (CIF-FOB), selected countries, GFI and study
Source: Authors' calculations based on CEPII, Trade Unit Values, and GFI 2021.

As mentioned, the addition of trade volumes and the resulting assessment of trade gaps can be compared to GFI, see **Figure 4.15** illustrating the differences for Gambia, Zambia, Côte d'Ivoire, and Kenya. It is, however, immediately apparent that the study's trade gaps are higher than GFI's, as they should be given that GFI excludes high-value CIF-FOB differences according to the criteria mentioned. Gambis is selected because it is the country with the highest trade gaps as assessed by GFI and the TFRI, not only in a singular year but throughout all the years encompassed by both studies.

In 2009-2018, the GFI assesses Gambia's value gap at an average of approximately 52% of its total bilateral trade, see **Figure 4.15**, marking the highest percentage evaluated for any country. In 2010-2019, this study assesses Gambia's value gap at an average of 56% of FOB value, or around USD 446 million per year, see **Figure 4.16**. Including insurance and transport costs, the study's assessed 56% is somewhat higher than GFI's 52%.

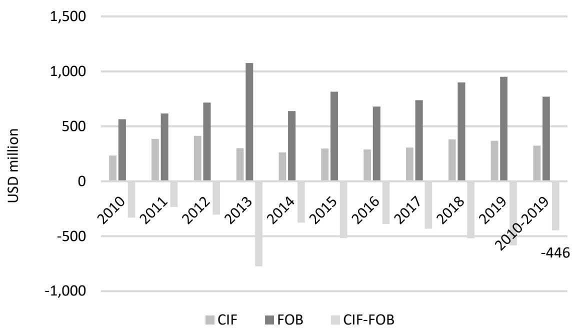


Figure 4.16: Trade gaps (CIF-FOB), Gambia, 2010-19
Source: Authors' assessments based on CEPII, Trade Unit Values and BACI.

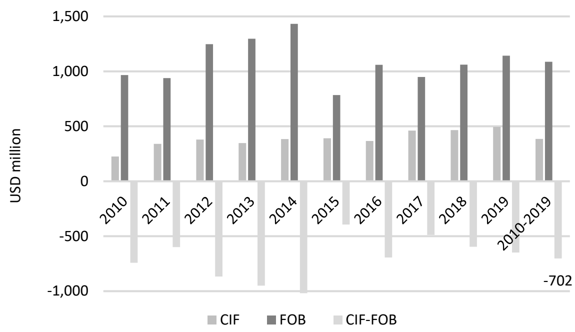


Figure 4.17: Trade gaps (CIF-FOB), UN COMTRADE, Gambia, 2010-19
Source: UN COMTRADE.

Using UNCOMTRADE instead of CEPII, the estimated annual trade gap for the period 2010-2019 is significantly higher, at USD 702 million compared to USD 446 million in the study, or around 64% of the assessed FOB values in the period 2010-2019, see **Figure 4.17**. Since UN COMTRADE also includes insurance and transport costs, it is potentially more aligned with the authors' assessed 56%.

Zambia is chosen to illustrate the discrepancies in the trade databases and the associated caution that should be taken when interpreting the results of the study and other studies based on the same databases. In 2012-2019, the study assesses Zambia's trade gap to average around USD 4.0 billion per year, or around 35% of FOB value, see **Figure 4.18**. In comparison, GFI assesses Zambia's value gap to be around 23% over the period 2012-2018. As the study's 35% includes insurance and transport costs, the difference with GFI's 23% is not necessarily significant.

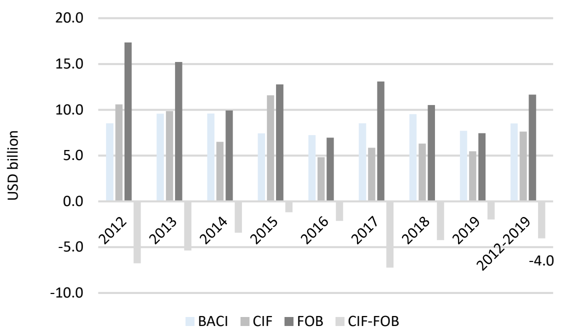


Figure 4.18: Trade gaps (CIF-FOB), authors and BACI, Zambia, 2012-19

Source: Authors' assessments based on CEPII, Trade Unit Values and BACI.

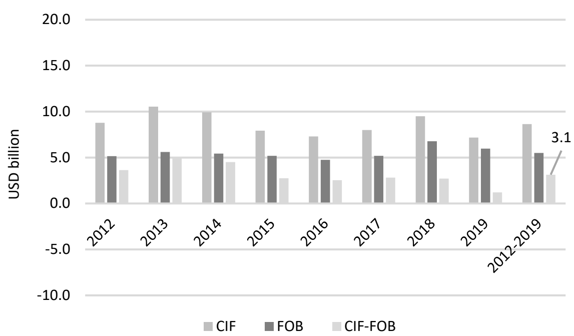


Figure 4.19: Trade gaps (CIF-FOB), UN COMTRADE, Zambia, 2012-19

Source: UN COMTRADE.

To illustrate discrepancies between databases, a similar assessment using UN COMTRADE data suggests that, conversely, CIF values are higher than FOB[12] values, resulting in a positive trade gap of around USD 3.1 billion for Zambia over the period 2012-2019, see **Figure 4.19**.

In addition, BACI trade values are used to control the assessed value of the CIF-FOB differences. The BACI trade values are so-called average "reconciled" values between the CIF values excl. insurance and transport costs and FOB values. This means that the BACI trade values should ideally lie in the range from slightly under the study's assessed CIF values incl. insurance and transport costs and up to the study's assessed FOB trade values. The criteria used by CEPII for averaging the CIF and FOB values are the assessed reliability of each country's reporting, while insurance and transport costs are removed using a gravity-type equation considering bilateral distance (in a non-linear manner), dummies for both contiguity and landlockedness, year fixed-effects, and the world median unit-value for each product category, see Gaulier and Zignago (2010). However, despite CEPII being the single source for the BACI values and the study results, BACI trade values are not consistently within the expected range. In 2015, they are significantly lower than the study's CIF value, and in 2016, they are higher than the study's FOB value, see **Figure 4.18**

Like Zambia. Cote d'Ivoire is chosen to illustrate the discrepancies between trade databases. In 2012-2019, the study assesses Cote d'Ivoire's trade gap to average around USD 1.9 billion per year, or around 16% of FOB value, see **Figure 4.20**. In comparison, GFI assesses Zambia's trade gap to be around 19% over the period 2012-2018. As the study's 16% includes insurance and transport costs, it should have been above the GFI's 23% and not below. Using UN COMTRADE similarly results in positive trade gaps for Côte d'Ivoire of around USD 0.9 billion over the period 2012-2019, see **Figure 4.21**.

[12] FOB values result from a UN Comtrade search with World as Reporter, country as Partner and Trade Flows as Export.

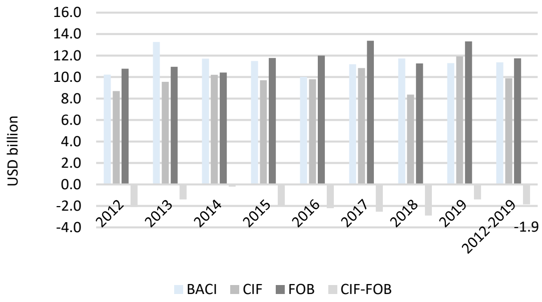


Figure 4.20: Trade gaps (CIF-FOB), authors and BACI, Côte d'Ivoire, 2015-19
Source: Authors' assessments based on CEPII, Trade Unit Values and BACI.

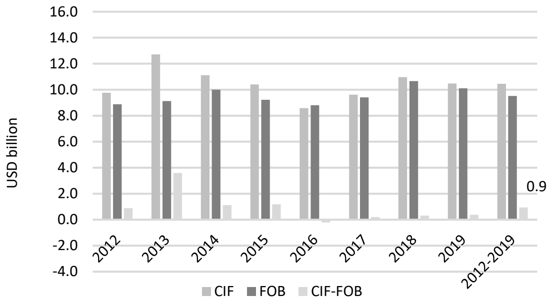


Figure 4.21: Trade gaps (CIF-FOB), UN COMTRADE, Côte d'Ivoire, 2015-19
Source: UN CCOMTRADE.

In summary, except for Côte d'Ivoire, most of the differences between the study and the GFI can probably be explained by the fact that GFI limits the variation in the CIF and FOB values and that this study includes insurance and transport costs. However, the use of UN COMTRADE data to assess trade gaps results in either significantly more negative value gaps than assessed in this study, as in the case of Gambia, or in positive value gaps, as in the case of Zambia and Côte d'Ivoire. Similarly, using BACI trade values as a control for this study's assessed CIF and FOB values does not consistently confirm the results, even though CEPII is the only source of these data. These observations suggest that there is some uncertainty in the trade gap assessments.

4.4 Kenya case study

Introduction

Kenya's import processes and customs enforcement underwent significant changes over the past two decades. The KRA data (220,000-250,000 customs declarations per year for 2015-2023) provide a granular view to test our methods. Applying the TFRI and trade gap analysis to Kenya yields insights into how policy and enforcement shifts have impacted fraud risk and revenue loss.

The frequency of CIF-FOB differences

The CIF/FOB ratios indicate improvements in Kenya's trade fraud risk. Comparing 2005 (first available year) and 2019 (last available year) shows a reduction in CIF/FOB ratios below one and an overall distribution moving closer to the Laplace distribution (centred around 1.0) associated with low-corruption contexts. **Figure 4.22** and **Figure 4.23** illustrate this shift, with far fewer instances of extreme undervaluation in 2019 than in 2005.

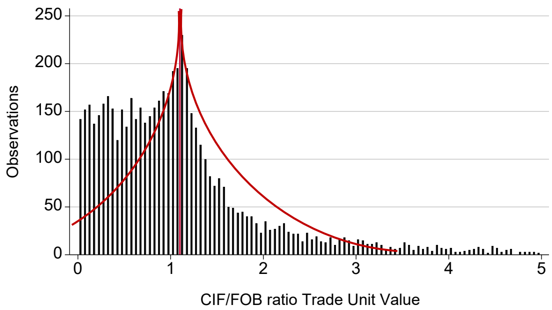


Figure 4.22: CIF/FOB ratios, Kenya, 2005

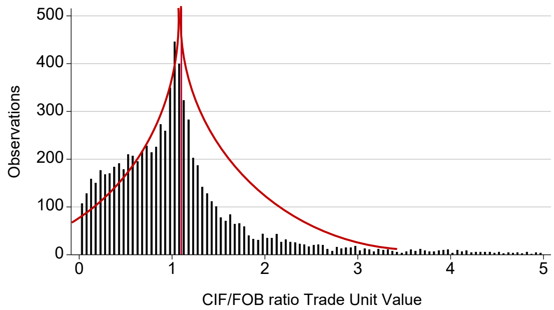


Figure 4.23: CIF/FOB ratios, Kenya, 2019

Source: Authors' assessments based on CEPII, Trade Unit Values.

This quantitative evidence suggests that the frequency of import undervaluation in Kenya has declined over time. The improvement coincides with various governance reforms and anti-corruption initiatives undertaken in Kenya. Notably, Kenya was the first country to ratify the United Nations Convention Against Corruption (UNCAC) in 2003, which came into force in 2005, and since then Kenya has implemented measures to strengthen institutional capacity against corruption.[13] Over the years, the Ethics and Anti-Corruption Commission (EACC) and other bodies have increased scrutiny of public officials, including customs officers. A United States Institute of Peace report found that civil society and non-governmental efforts in Kenya have also played a role in monitoring and exposing corruption in public offices (USIP, 2019). Furthermore, according to Transparency International's CPI data, Kenya's score modestly improved in the late 2010s compared to the mid-2000s, reflecting slow progress in curbing corruption.[14]

Nevertheless, a United States Institute of Peace (USIP) report concludes that foreign donors, especially bilateral and multilateral organizations, are sending conflicting messages regarding the priority of combating corruption in Kenya. Consequently, certain Kenyan organizations and individuals engaged in initiatives related to transparency, accountability, and good governance hesitate to adopt a more assertive position against corruption. (USIP, 2019).

Finally, according to Transparency International's CPI, Kenya has made a somewhat modest improvement from 144 out of 180 countries in 2005 to 137 out of 180 countries in 2019 and further to 123 out of 180 countries in 2022.[15] Nevertheless, the CIF/FOB ratios indicate a significant improvement in the trade fraud risk between 2005 and 2019.

[13] UNODC, see: https://www.unodc.org/easternafrica/en/Stories/unodc-lauds-anti-corruption-efforts-in-kenya.html
[14] EACC, see: https://eacc.go.ke/default/partnership/
[15] Transparency International, see https://www.transparency.org/en/cpi/2022/index/ken

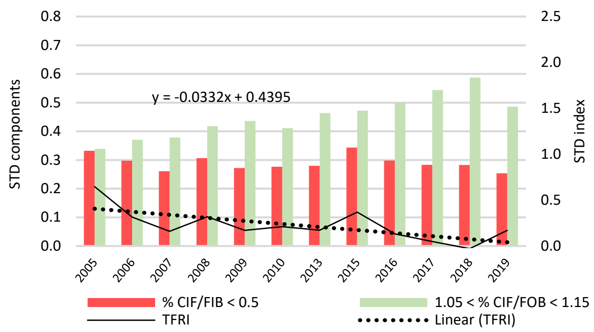


Figure 4.24: TFRI and components, Kenya, 2005-2019
Source: Authors' assessments based on CEPII, Trade Unit Values.

This improvement is perhaps more evident in the TFRI and its components, see **Figure 4.24**. The percentage of CIF/FOB ratios below 0.5 has decreased, while the percentage of CIF/FOB ratios between 1.05 and 1.15 has increased, although it drops abruptly in 2019. Overall, this results in a significant improvement in the TFRI over the period, falling from an index value of 0.65 in 2005 to 0.15 in 2019 (-0.03 in 2018). This is also illustrated by the linear trend line with a negative slope of -0.033 and a constant of 0.44.

Compared to other EAC countries, Kenya has managed to reduce the frequency of imports with CIF/FOB ratios below 0.5, i.e., potential undervaluation, and to increase the frequency of imports with CIF/FOB ratios between 1.05 and 1.15, i.e., around the level of expected transport and insurance costs, considerably more than Tanzania and Uganda, see **Figure 4.25** and **Figure 4.26**. And while Tanzania and Uganda also have experienced improvements in their trade fraud risk in the period, their TFRI values were around 1.0-15 in 2018 (latest year), while Kenya's corresponding value was around -0.03, see **Figure 4.24**.

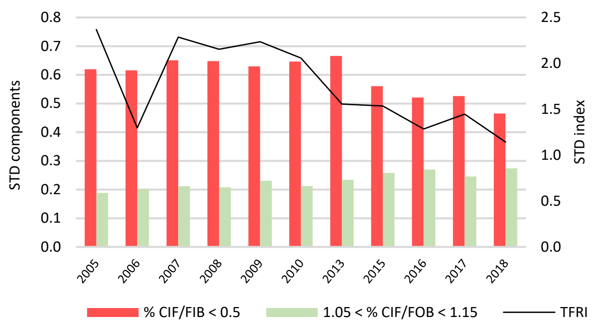


Figure 4.25: TFRI and components, Tanzania, 2005-2018
Note: To enhance comparison, only years with data for Kenya are included.
Source: Authors' assessments based on CEPII, Trade Unit Values.

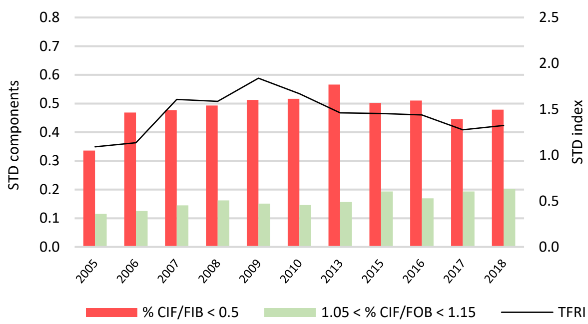


Figure 4.26: TFRI and components, Uganda, 2005-2019
Note: To enhance comparison, only years with data for Kenya are included.
Source: Authors' assessments based on CEPII, Trade Unit Values.

The value of CIF-FOB differences

The reduction in the frequency of CIF-FOB differences has also had an impact on the value of these differences, i.e. on Kenya's trade gap. Subject to the uncertainties discussed and data availability, it is assessed that Kenya had a value gap of around minus USD 9.9 billion in 2015 but that it has been reduced to around minus USD 1.4 billion in 2019, see **Figure 4.27**.

Over the period 2015-2018 (the comparable period for GFI), Kenya's average trade gap is assessed at around minus USD 7.3 billion, corresponding to around 26% of the assessed FOB values over the period. In comparison, GFI assesses Kenya's trade gap at around 24% of total trade over the period 2015-2018. According to UN COMTRADE, Kenya's trade gap was smaller at around minus USD 2.9 billion in 2015 and around minus USD 1.1 billion in 2019, representing around 9% of assessed FOB values over the period, see **Figure 4.28**. Despite the UN COMTRADE trade gap including insurance and transport costs, it is likely to represent the relatively lowest among the three assessments.

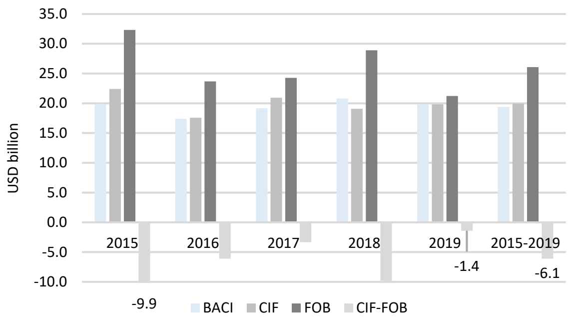


Figure 4.27: Trade gaps (CIF-FOB), authors and BACI, Kenya, 2015-2019

Source: Authors' assessments based on CEPII, Trade Unit Values and BACI.

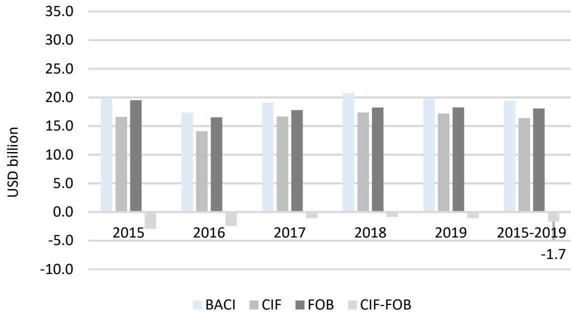


Figure 4.28: Trade gaps (CIF-FOB), UN COMTRADE, Kenya, 2015-2019

Source: UN COMTRADE.

It is noteworthy that the CIF and FOB values by UN COMTRADE are consistently lower than the reconciled BACI bilateral trade values, while the BACI values are more aligned with the authors' assessed CIF and FOB values. As CIF and FOB values are based on BACI volumes, the latter was expected, but the discrepancy between UN COMTRADE and BACI is not, see **Figure 4.27** and **Figure 4.28**.

Using the KRA data, it is possible to compare CIF import values assessed by the study with Kenya's actual CIF import values, see **Figure 4.29**. This comparison shows that the study's assessed CIF import values are around USD 3-7 billion higher per year for the period 2015-2019 than the actual CIF import values. This is higher than the BACI reconciled bilateral trade values and much higher than the UN COMTRADE CIF values that are relatively closest to the KRA CIF values. However, when volumes are added to the comparison, it follows that the study's assessed CIF values are based on higher trade volumes than the KRA CIF values, see **Figure 4.30**.

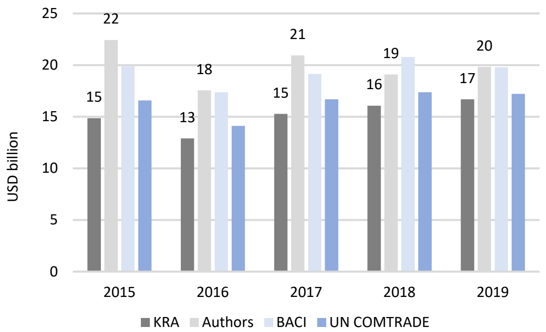


Figure 4.29: CIF values, KRA, authors, BACI and UN COMTRADE, Kenya, 2015-2019

Source: Authors' assessments based on CEPII, Trade Unit Values and BACI, UN COMTRADE, and KRA.

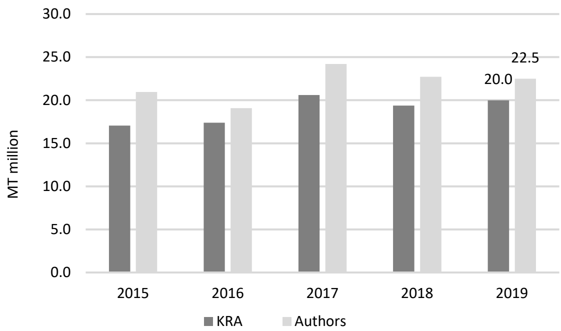


Figure 4.30: CIF volumes, KRA and BACI, Kenya, 2015-2019

Source: Authors' assessments based on CEPII, Trade Unit Values and BACI, and KRA.

Roughly half of the differences in the CIF trade values between the KRA and this study are assessed to be due to differences in trade volumes, while the other half is currently unexplained. In 2019, KRA's total CIF volume was around 20.0 million MT, while UN COMTRADE's was around 19.4 million MT (FOB volume is used as CIF volume is missing) and BACI's (used by the authors) was around 22.5

million MT. These differences clearly show the uncertainty that surrounds these assessments. For example, the BACI's figure of around 22.5 million MT in 2019 is an average between CIF and FOB. However, with UN COMTRADE's FOB volumes of around 19.4 million MT and KRA's CIF volumes of around 20.0 million MT, it is difficult to connect the dots between these sources.

Potentially lost tariff revenue

With these uncertainties in mind, the next step is to try to assess the associated potentially lost tariff revenue due to the assessed trade gaps. This is done using WTO tariff rates at the 4-digit level, which means that the potentially lost tariff revenue can be assessed at a relatively detailed industry level.

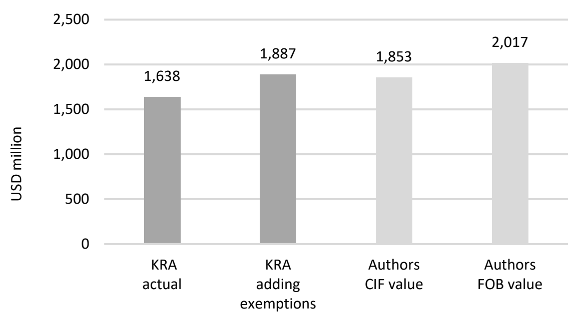


Figure 4.31: Tariff revenue, KRA and authors, 2019

Source: Authors' assessments based on CEPII, Trade Unit Values, WTO tariff rates and KRA.

In 2019, KRA reported a total tariff revenue of around USD 1,638 million. This included around 40,540 exemptions, where customs declarations for various reasons were exempted from tariffs. Cancelling these exemptions and adding them to the tariff revenue results in a total of around USD 1,887 million. In comparison, the authors assessed that total tariff revenue was around USD 1,853 million when based on CIF trade value, and around USD 2,017 billion when based on FOB trade value, see **Figure 4.31**.

Since the assessed tariff revenue cannot consider the exemptions imposed by the KRA, the relevant comparison is between the KRA's figure of USD 1,887 million, which includes tariff revenue from exempted customs declarations, and this study's assessment of USD 1,853 million CIF-based tariff revenue. The closeness of the two tariff revenue figures, despite a difference of around USD 3 billion in the underlying CIF trade value, see **Figure 4.29**, calls for further investigation.

While variations in total CIF trade value may not always result in differences in total tariff revenue, this outcome is contingent upon the CIF trade value and the applied tariff rates for each product category. Conversely, an analysis of the CIF trade value and the applied tariff rates reveals numerous disparities between the KRA and the study, despite both parties employing CIF values and tariff rates at the HS 4-digit level. The proximity of the two tariff revenue figures is solely due to the offsetting nature of these differences.

In summary, due to the differences in CIF values and applied tariff rates between the KRA's and the study, the most robust assessment of lost tariff revenue is given by the difference between the study's assessed CIF and FOB tariff revenues. This ensures that volumes and tariff rates are identical, with the only variable being unit trade values.

In 2019, this suggests a potential net tariff revenue loss for Kenya of around USD 164 million. Whether this is a fair figure for Kenya is difficult to determine due to data gaps, see **Figure 4.32.** Since 2015, and assuming 2018 to be an outlier, the estimated net tariff revenue loss for Kenya has been significantly reduced. Conversely, if 2017 and 2019 are assumed outliers and 2015, 2016 and 2018 are assumed accurate for the period, Kenya has had no reduction in its net tariff revenue loss.

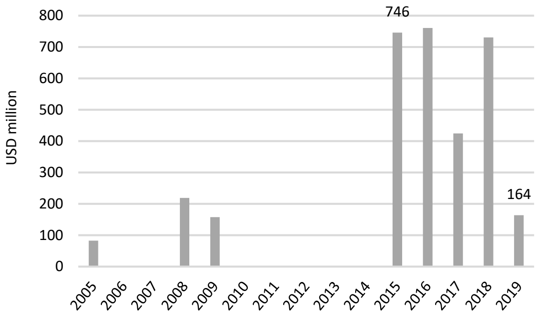


Figure 4.32: CIF & FOB tariff revenue differences, Kenya, 2005-2019

Source: Authors' assessments based on CEPII, Trade Unit Values.

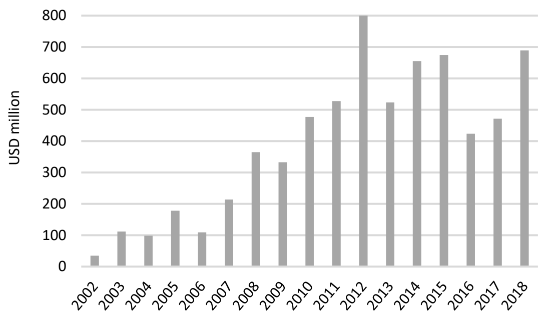


Figure 4.33: CIF & FOB tariff revenue differences, Tanzania, 2002-2019

Source: Authors' assessments based on CEPII, Trade Unit Values.

However, looking instead at the CIF-FOB difference as a percentage of the FOB trade value, it appears that 2018 is the outlier and that Kenya has indeed experienced a reduction in its trade gaps, from around 31% in 2015 to around 7% in 2019, see **Figure 4.34**. In comparison, Tanzania has had a relatively constant estimated trade gap varying around an average of 30%-40% over the period 2002-2018, see **Figure 4.35**. As Tanzania's imports have increased more than six-fold over this period, this means a significant increase in its net tariff revenue loss, see **Figure 4.33**.

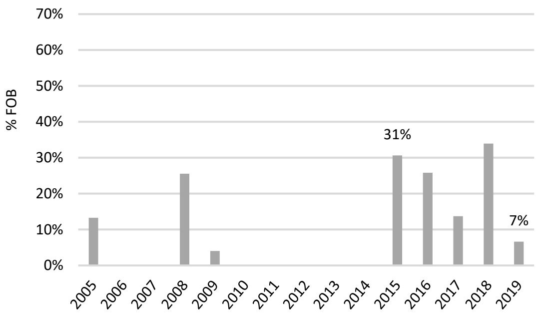


Figure 4.34: CIF & FOB difference as percentage of FOB trade value, Kenya, 2005-2019

Source: Authors' assessments based on CEPII, Trade Unit Values and BACI, UN COMTRADE and WTO tariff rates.

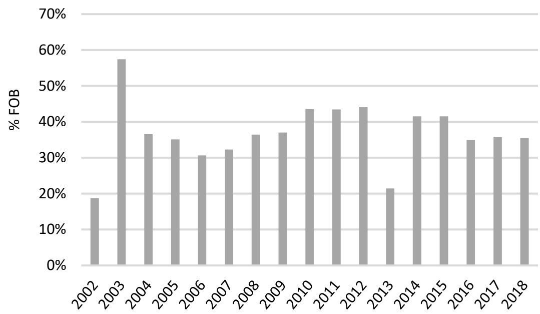


Figure 4.35: CIF & FOB difference as percentage of FOB trade value, Tanzania, 2002-2019

Source: Authors' assessments based on CEPII, Trade Unit Values and BACI, and WTO tariff rates.

While net CIF-FOB tariff revenue differences, including both positive and negative values, are assessed at around USD 164 million, total negative CIF-FOB tariff revenue differences are assessed at around USD 307 million. At HS 2-digit level, a total of 48 out of 96 CIF-FOB tariff revenue differences are assessed to be negative, with the top 10 totalling around negative USD 206 million, see **Figure 4.36** and **Figure 4.37**.

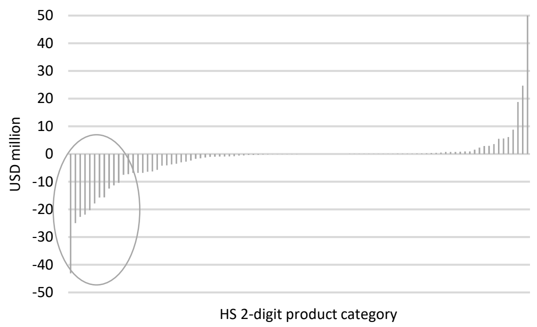


Figure 4.36: Tariff CIF-FOB differences, HS 2-digit, Kenya, 2019

Source: Authors' assessments based on CEPII, Trade Unit Values and BACI, UN COMTRADE and WTO tariff rates.

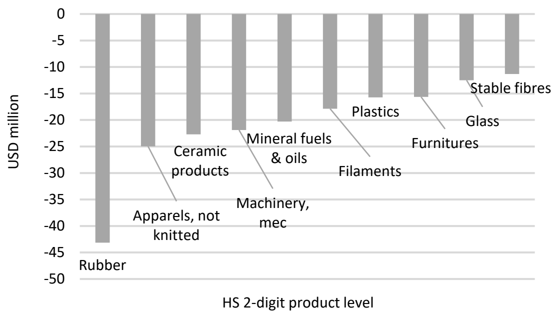


Figure 4.37: Top-10 Tariff CIF-FOB differences, HS 2-digit, Kenya, 2019

Source: Authors' assessments based on CEPII, Trade Unit Values and BACI and WTO tariff rates.

Among the top 10 are sectors often associated with fraud such as textiles, mineral oil, and manufactured products (WTO, 2015 and Grigoriou, 2019). By way of illustration, the KRA CIF value for the five largest textile HS 2-digit sectors given in terms of HS 60-65 was around USD 446 million, while the corresponding assessed FOB value was around USD 1,450 million, indicating significant undervaluation. Similarly, the KRA CIF value for a manufacturing sector such as plastics was around USD 753 million, while the corresponding assessed FOB value was around USD 1,200 million.

At HS-2 level, the third largest negative tariff CIF-FOB difference was for the ceramics sector, see **Figure 4.37**. At HS 4-digit level, it is further possible to detect which underlying industry groups generate these negative differences.

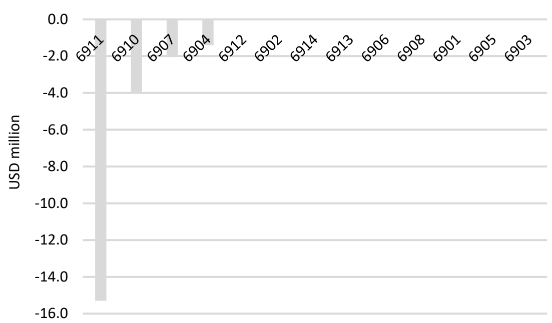


Figure 4.38: Tariff CIF-FOB differences, HS 4-digit level ceramics products, Kenya, 2019

Source: Authors' assessments based on CEPII, Trade Unit Values, and WTO tariff rates.

The biggest contributor, with an assessed minus USD 15.3 million, is HS6911 "Tableware, kitchenware, other household articles and toilet articles; of porcelain or china" was the most significant contributor, see **Figure 4.38**. The second biggest contributor, with an assessed minus USD 3.9 million, is HS6910 "Ceramic sinks, wash basins, wash basin pedestals, baths, bidets, water closet pans, flushing cisterns, urinals and similar sanitary fixtures," also contributed. At this level of detail, the results could be useful in terms of highlighting potentially fraudulent practices for certain import industries.

In summary, Kenya's trade fraud risk has improved over the period 2005-2019. Its CIF/FOB ratios are in transition from the log-normal distribution to the Laplace distribution, which is otherwise associated with high-income/low-corruption countries. The associated TRFI shows a significant improvement, falling from an index value of 1.2 in 2005 to 0.4 in 2019 (0.1 in 2018). In parallel, Kenya's potential tariff revenue loss, measured as the difference between tariff revenue from CIF import value and FOB export value, has declined from around USD 746 million in 2015 to around USD 164 million in 2019, while its CIF-FOB trade gap has declined from 31% to 7%. In comparison, Tanzania has had a relatively constant estimated trade gap varying around an average of 30%-40% over the period 2002-2018.

4.5 Field observations from the Port of Mombasa

To better understand the mechanisms behind these quantitative patterns, an exploratory field study was conducted at the Port of Mombasa in late 2024. Researchers visited Kenya's largest port from November 19-28, 2024, meeting with a range of stakeholders including customs clearing agents, container freight station (CFS) staff, truck drivers, and others. In total, the field team visited three CFS facilities and the main port entry, and held semi-structured interviews with four clearing agents, multiple CFS employees, ten truck drivers, and other port workers. This qualitative inquiry offers ground-level insight into Kenya's import process and how misreporting practices lead to revenue loss, complementing the Trade Fraud Risk Index (TFRI) results with on-the-ground observations.

Kenya's import procedure involves multiple agencies (KRA, KEBS, KPA, etc.) and documentation at various stages. Critically, the system relies on self-declaration: importers (or their clearing agents) submit declarations of cargo quantity, type, and value via the Integrated Customs Management System (iCMS), supported by invoices and packing lists. Customs authorities verify quantities and cargo content relatively easily through weighbridges and scanners at port entry, but determining the true value of goods is far more challenging. All containers are weighed and scanned on arrival, and any discrepancy between the shipment's manifest and its actual weight or image triggers a flag for inspection. Officially, a flagged shipment must undergo a joint physical inspection by KRA (along with KEBS and other agencies as relevant), yet in practice a KRA supervising officer can decide to waive or clear a shipment despite irregularities. Field interviews revealed that this discretion is often exploited through informal arrangements, allowing some importers to evade full inspections and scrutiny.

The Mombasa fieldwork highlighted several fraudulent tactics used to evade duties and taxes:

(i) Undervaluation of imports: The most prevalent scheme is under-declaring the value of goods. For example, an importer might declare a shipment of 1,000 items at KSh 10 each when the true market value is KSh 40 each. Since invoices are not standardized and customs officers have limited ability to verify true prices, such under-valuation often goes undetected unless a detailed inspection is carried out.

(ii) Misclassification of tariff lines: Importers also misreport goods under incorrect HS codes to attract lower tariff rates. A prominent case involved the misclassification of refined palm oil (subject to 35% import duty) as crude palm oil (10% duty), enabling the importer to pay the lower rate. This single scheme was alleged to have cost Kenya around KSh 62 billion (≈ USD 480 million) in lost revenue, illustrating how significant the impact of classification fraud can be.

(iii) "Facilitation" bribes for speedy clearance: Customs clearing agents can often make informal payments to KRA officials to expedite the release of cargo. Such facilitation payments may be coercive (to release goods that officers intentionally delay to extract a bribe) or collusive (proactively paid to prioritize urgent or perishable shipments). By "greasing" the process, clearing times can shrink dramatically (in some reports, to under 30 minutes for certain containers), helping importers avoid storage fees and time-sensitive losses. These payments, although unofficial, are often viewed by agents as a necessary cost of doing business when faced with slow or obstructive customs procedures.

(iv) Bribes to avert inspection flags: When port scanners or weight checks detect an anomaly, a KRA Verification Officer is tasked with flagging the shipment in the iCMS system for inspection. However, interviews indicated that clearing agents sometimes pre-empt this by directly negotiating with the verification officer. In exchange for a bribe, the officer will refrain from officially flagging the discrepancy. This under-the-table resolution means the issue is "fixed" informally: the importer pays some monetary compensation (often much less than the formal duty or fine that would be due) to the officer, part of which would otherwise have gone to the public treasury. Crucially, the problematic shipment avoids entering the formal inspection workflow, escaping the oversight of higher authorities who are required to clear any official flags.

(v) Collusion during physical inspections: Even when a container is formally flagged and opened for inspection, illicit facilitation can subvert the outcome. Clearing agents described instances of bribing the inspection team (which includes KRA, KEBS, and other agency officers) to overlook undeclared or undervalued items. In practice, inspectors have been bribed to upload only benign photos of the cargo (for example, images of goods that match the manifest) into the iCMS as "proof" of compliance, omitting any incriminating evidence. By falsifying inspection records, the undeclared goods pass through as if all were in order. Such collusion not only lets undervalued imports through but also diverts what should have been tax revenue into private hands. Notably, KRA supervising officers are typically aware of these off-record dealings; they often sanction the arrangement and take a share of the illicit payments, coordinating with verification officers under their command.

The field research also sheds light on the key institutional actors and their roles in either enabling or curbing misreporting:

(a) Customs Clearing Agents: These licensed agents are the intermediaries between importers and the state's customs apparatus. Because clearing agents handle the paperwork and physical process for goods through the port, they have intimate knowledge of any irregular practices. Interviews confirmed that agents are frequently the ones who arrange for informal payments on behalf of importers, given their constant interactions with KRA officers. With over 1,000 registered clearing agencies in Kenya, their collective experience is central to understanding port fraud. Engaging this group is crucial for reforms, as they have a vested interest in a more efficient and transparent system (which would level the playing field and reduce "unofficial" costs).

(b) Kenya Revenue Authority (KRA): The KRA is the lead government body managing customs at the Port of Mombasa. It operates through departments overseeing enforcement (cargo scanning and weighing), verification (inspecting flagged shipments and investigating discrepancies), and clearance, all under a hierarchy ending with supervising officers. KRA officers are present at every critical checkpoint of the import process, from the gate to final clearance. Field evidence suggests that while many KRA officials perform diligently, some abuse their positions by soliciting or accepting bribes to bypass procedures. For instance, a verification officer can be persuaded to clear a mis-declared shipment or to report false inspection results, as described above. Such actions undermine the enforcement mechanisms that KRA has put in place.

(c) Kenya Bureau of Standards (KEBS): KEBS inspectors are tasked with ensuring imported products meet Kenyan standards and are often involved in inspections. Uniquely, KEBS conducts pre-shipment inspections in exporting countries and again inspects goods upon arrival, providing a double layer of quality control. This dual inspection regime could, in theory, help catch irregularities (for example, if goods differ from what was certified abroad). However, the field interviews did not reveal clear cases of KEBS officials engaging in fraud at Mombasa. It remains an open question whether KEBS procedures significantly deter misreporting; further research directly with KEBS personnel could shed light on their role at various ports.

(d) Container Freight Stations (CFSs): CFSs are privately-operated off-port facilities where importers can opt to have their containers transferred for clearance after arrival. These stations act as extensions of the port, offering importers longer free storage time and potentially less congestion during the clearing process. KRA officers are posted at CFSs to conduct inspections and process clearances, though final approvals are done by off-site supervisors. The field visits to CFSs indicated that, because final clearance officers are not physically present, clearing agents and CFS staff sometimes face delays and extra coordination to get shipments released. There were suggestions that informal payments may be just as prevalent in CFS settings as at the port, but this may vary by station. The differing procedures and autonomy at CFSs versus the main port present an interesting comparative angle for how misreporting might be facilitated or curbed in each setting.

(e) Other Stakeholders: Several other entities influence the import process. The Kenya Ports Authority (KPA) manages port operations (e.g., container handling) but does not control the release of goods. The Kenya Maritime Authority and Kenya Coast Guard oversee maritime traffic and security in Port waters. While these bodies are not directly involved in customs valuation, their efficiency can indirectly affect opportunities for fraud; delays or bureaucratic hurdles in one part of the chain can incentivize “shortcuts” elsewhere. Shipping companies also play a role: they generate key documents (like the Bill of Lading) and control container logistics. Field informants noted that shipping lines and agents are stakeholders in improving port integrity, since consistent fraud and delays can disrupt their operations too.

Overall, the Mombasa fieldwork underscores that Kenya’s improvements in curbing trade fraud, reflected quantitatively by a shrinking CIF-FOB gap, are the product of an ongoing struggle. The import process has modernized (for instance, through iCMS and scanning technology), and indeed Kenya’s trade fraud risk has measurably declined. Yet the qualitative evidence makes clear that informal networks and rent-seeking behaviours persist.

Even as average undervaluation frequency dropped, individual cases like the reported misclassification of palm oil show how fraudulent actors adapt to exploit specific loopholes, sometimes with substantial payoff. Likewise, the continued prevalence of bribery at various checkpoints indicates that certain officials and traders still find it mutually beneficial to circumvent formal controls.

These ground-level insights lend context to the TFRI’s findings. They explain how the “risk” captured by the index materializes in practice. Notably, the largest value discrepancies tend to occur in products and situations where the incentives to cheat are high (e.g., high-tariff goods, perishable shipments facing deadlines), and oversight can be negotiated away. Integrating such qualitative understanding with quantitative risk indices like the TFRI allows policymakers to better target the root causes of misreporting. Strengthening enforcement will require not just data analytics and random inspections, but also institutional reforms, such as rotating officers, enhancing accountability, and leveraging technology to reduce human discretion, aimed at closing the very avenues of collusion identified by the field study.

5 Discussion/Conclusion

The findings presented in this study (combining distributional analysis of CIF-FOB ratios, the construction of a Trade Fraud Risk Index (TFRI), assessments of CIF-FOB trade gaps, and qualitative field insights from the Port of Mombasa) underscore the importance of integrating quantitative and institutional perspectives when analysing trade fraud risk. This discussion situates the empirical results within the wider literature on customs administration, illicit financial flows, and regulatory governance, and highlights the methodological, policy, and conceptual implications of the study.

Interpreting CIF-FOB Distributions and the TFRI in the Context of Governance and Trade Integrity

A central empirical contribution of this study is the identification of robust distributional regularities in CIF-FOB trade unit value ratios across countries. The emergence of three distinct regimes reflects systematic differences in customs valuation practices, trade cost environments, reporting accuracy, and institutional integrity. The clustering of high-income, low-corruption countries around Laplace-type distributions is consistent with the expectation that customs declarations in these contexts tend to reflect more accurate valuation practices, limited manipulation, and more reliable enforcement mechanisms. By contrast, the prevalence of exponential-type distributions among lower-income and high-corruption countries aligns with the hypothesis that undervaluation and misreporting are more frequent in settings where administrative capacity is constrained, and enforcement incentives are weaker.

The resulting TFRI synthesises these distributional insights into a single, interpretable measure of trade fraud risk. Importantly, the index demonstrates only partial correlation with broad corruption measures such as Transparency International's Corruption Perceptions Index (CPI). This divergence suggests that the TFRI captures a more specific dimension of governance, namely, fraudulent behaviour in customs valuation, which may not move in tandem with general perceptions of public-sector integrity. This finding aligns with the argument in the institutional economics literature that sector-specific corruption does not necessarily co-move with aggregate governance indicators, particularly when reforms are unevenly targeted or when administrative improvements outpace broader political governance changes.

The case of Kenya illustrates this divergence. Despite only modest improvements in CPI scores over the past decade, Kenya's TFRI demonstrates a marked transition from a lognormal to a near-Laplace distribution between 2005 and 2019, signalling a substantial reduction in the frequency of undervaluation. This suggests that reforms in revenue administration, digitalisation of customs processes, and improved risk-management systems likely have had tangible effects on trade valuation integrity, even if broader anti-corruption performance remains stagnant.

Value-Gap Estimation, Revenue Loss, and Data Reliability

Beyond the analysis of distributional patterns, this study estimates the monetary value of CIF-FOB differences by combining trade unit values with harmonised trade volumes and applying WTO tariff rates. These estimates suggest that Kenya's CIF-FOB trade gap declined significantly between 2015 and 2019. When expressed as a share of FOB values, the gap decreased from approximately 31% to around 7%. This decline also manifests in the estimated potential tariff revenue losses, which fell from approximately USD 746 million in 2015 to roughly USD 164 million in 2019. However, the discussion must also acknowledge the considerable uncertainty and variability in value-gap estimations arising from differences across datasets. As demonstrated in the comparisons between CEPII-based assessments, UN COMTRADE data, and Global Financial Integrity results, varying datacleaning protocols, transformations of CIF to FOB values, and criteria for retaining or excluding outliers can materially influence estimated trade gaps. The discrepancies observed for Zambia, Côte d'Ivoire, and even Kenya underscore the limits of interpreting any single dataset or methodological approach as definitive. This reinforces the argument, common in the literature on illicit financial flows, that multiple estimation techniques should be triangulated and interpreted cautiously, particularly when used to inform policy or enforcement actions.

Notwithstanding these limitations, the consistency with which the TFRI and the Kenya Revenue Authority's (KRA) administrative data point to declining undervaluation risk strengthens confidence in the overall direction of Kenya's progress. The convergence between declining CIF-FOB gap ratios and qualitative reports of improved procedural controls (e.g., greater use of non-intrusive inspection technologies, partial digitalisation of workflows) suggests that genuine institutional improvements have taken place. Yet the persistence of data discrepancies emphasizes the need to interpret absolute revenue-loss figures with caution and to focus more on relative changes, distributional shifts, and patterns of risk across product categories.

Insights from Qualitative Fieldwork: Mechanisms, Incentives, and Institutional Dynamics

The integration of qualitative fieldwork into the analysis provides a uniquely grounded perspective on how undervaluation and misreporting occur in practice. While many quantitative studies of trade mis-invoicing focus solely on statistical anomalies, the field observations offer an essential micro-institutional complement. They demonstrate that undervaluation is not merely a statistical artefact, but a behaviour shaped by incentives, organisational structures, and opportunity spaces within the customs environment. Several themes emerge from the fieldwork:

(a) The centrality of discretion and procedural bottlenecks

Customs officers (especially verification officers and supervising officers) retain considerable discretionary authority in deciding whether to flag shipments for inspection, waive inspections, or accept documentary evidence at face value. Such discretion is a double-edged sword: In principle, it enables efficient processing of compliant shipments; in practice, it creates opportunities for manipulation and informal payments. Interviews suggest that delays, bureaucratic hurdles, and congestion increase the value of discretionary acceleration, generating incentives for facilitation payments.

(b) Information asymmetry between importers and the state

Clearing agents, importers, and freight stations often possess superior knowledge of product quality, true market prices, and the likelihood of inspection. Customs officers, despite scanner data and weight checks, face constraints in verifying value declarations, especially for heterogeneous goods such as ceramics, electronics, or used clothing. This asymmetry fosters undervaluation: importers exploit gaps in official valuation databases and inconsistencies in reference pricing.

(c) Collusive practices in inspection and verification

Field interviews point to repeated instances of collusion during physical inspections, including selective photography of containers, manipulation of inspection reports, and negotiation of settlement payments outside official channels. These practices undermine the enforcement mechanisms that the TFRI implicitly assumes support the accuracy of declared values.

(d) Sector-specific vulnerabilities linked to tariff structures

The fieldwork sheds light on why certain sectors (such as textiles, plastics, and ceramics) appear particularly prone to undervaluation in the quantitative results. These sectors combine high tariff differentials, ease of misclassification, and, in some cases, large and fragmented supply chains, creating ample opportunities for fraud. For instance, the widely reported misclassification of refined palm oil as crude palm oil aligns with the substantial tariff spread between these products and illustrates the substantial fiscal consequences of classification manipulation.

Collectively, these insights emphasize that improvements in aggregate indicators such as the TFRI do not eliminate the operational vulnerabilities that sustain fraud. Rather, they point to the coexistence of systemic improvements with persistent pockets of resistance within the customs system, consistent with theories of bounded reform and partial bureaucratic modernisation.

Integrating Quantitative and Qualitative Evidence: Implications for Methodology

The study's dual-method design has important implications for future research on trade fraud and illicit financial flows. The quantitative analysis provides breadth and comparability across countries and years, while the qualitative findings provide depth and explanatory granularity. This triangulated approach addresses several limitations in the existing literature:

- It highlights that statistical anomalies must be interpreted with attention to institutional context (a point often overlooked in mirror-trade analyses).
- It reveals why sectoral risk varies widely within countries, supporting a movement toward more granular, HS-level or even firm-level risk modelling.
- It shows that improvements in customs systems may not be uniform; administrative modernisation can reduce average undervaluation while corruption networks persist in specific product lines or operational nodes.

This methodological complementarity suggests that future work on trade integrity would benefit from integrated approaches that combine large-scale statistical diagnostics with institutional ethnography, administrative data analysis, and field-based insights.

Policy Implications: Targeted Enforcement, Institutional Reform, and Cross-Agency Coordination

The combined evidence from the TFRI, trade-gap analysis, and fieldwork carries several implications for customs administrations and policymakers:

(i) Sector-targeted risk management

Given the heterogeneity across HS categories, targeted interventions, such as enhanced valuation protocols for textiles, ceramics, petroleum products, and electronics, may yield greater fiscal returns than broad, undifferentiated enforcement.

(ii) Strengthening digital and non-intrusive inspection systems

While Kenya has expanded scanning and electronic filing, field evidence shows that the benefits can be undermined by discretionary overrides. Reducing reliance on officer discretion and strengthening audit trails in iCMS could limit opportunities for collusion.

(iii) Reforming the governance of discretionary authority

Clearer protocols governing when inspections may be waived, combined with automated risk-trigger mechanisms that cannot be manually overridden, would reduce opportunities for rent extraction.

(iv) Addressing incentives for informal payments

Delays and unpredictability in clearance processes generate demand for facilitation payments. Policies aimed at reducing procedural bottlenecks, such as harmonising KRA, KEBS, and KPA operational workflows, would diminish such incentives.

(v) Enhancing inter-agency accountability

The fieldwork highlights fragmented responsibilities across customs, standards, and maritime authorities. Stronger coordination, potentially through joint audit teams or integrated digital platforms, could reduce opportunities for conflicting mandates to be exploited.

The findings contribute to broader theoretical debates in several ways. They support the hypothesis that sector-specific corruption and fraud risks can be decoupled from aggregate corruption measures. They demonstrate how institutional reforms can yield measurable improvements in trade data even when broader governance indicators remain stagnant. Finally, they show how incentives and organisational cultures shape compliance outcomes, echoing arguments in the political economy literature that reforms are often partial and path-dependent.

Overall, this study demonstrates that progress in reducing trade fraud is possible, measurable, and detectable both statistically and on the ground. Kenya's experience illustrates how targeted reforms (digitalisation, improved risk management, enhanced scanning, and procedural streamlining) can meaningfully reduce undervaluation. However, persistent micro-level vulnerabilities identified in the fieldwork highlight the need for continued vigilance and institutional strengthening. The TFRI, complemented by qualitative assessments, provides a valuable framework for diagnosing and monitoring such vulnerabilities.

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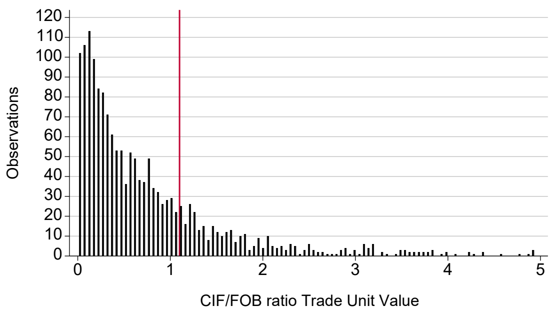
Appendix A: Robustness check of the TFRI

No firm criteria exist for determining the ranges of the two components in the TFRI. Component 1 targets low-income/high-corruption countries with a significant imbalance in CIF/FOB ratios, where most CIF values are lower than the corresponding FOB value, i.e., a high degree of under- and/or overvaluation of imports and exports and potential loss of customs revenue. Component 2 targets high-income/low-corruption countries, where under- and/or overvaluation of imports or exports is relatively low and where most of the differences between the CIF and FOB values can be attributed to insurance and transport costs.[16] For high-income countries, this typically implies a relatively low CIF/FOB ratio because high-income countries often have a higher percentage of high-value imports such as manufactured goods, reducing the relative percentage of insurance and transport costs, see e.g. Chasomeris (2009).

The distributions of the CIF/FOB ratios show that Component 1 should measure the percentage of CIF/FOB ratios somewhere below 1.0 to capture the low-income/high-corruption countries, see **Figure 6.1**, while Component 2 should measure the percentage of CIF/FOB ratios somewhere around 1.0, see **Figure 6.2**.



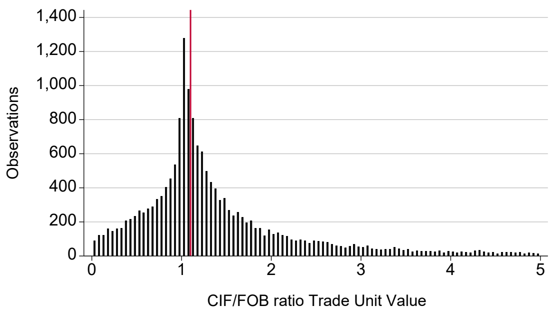


Figure 6.1: CIF/FOB ratios, Sierra Leone, 2018 **Figure 6.2: CIF/FOB ratios, Japan, 2019**

Note: Red line at CIF/FOB ratio of 1.1 marks a potential 10% insurance and transport costs.

Source: Authors' calculations based on CEPII, Trade Unit Values.

As this leaves ample scope for setting the ranges of the two components, different range values have been applied to test the robustness of the TFRI's country rankings according to component ranges, see **Table 6.1**, where component 1 is set to vary from 0.30 to 0.70, and component 2 is set to vary from 0.90 to 1.20.

For the top 10 countries with the highest risk of under- and/over valuation of imports and exports, a total of 12 different countries are included out of a potential 50 countries across the five different component ranges. This means that there is a lot of repetition among the countries and therefore a high robustness with respect to country ranking and different values of the component range. The same applies to the bottom 10 countries with the lowest risk of under- and/over valuation of imports and exports, where a total of 15 different countries are included out of a potential 50 countries.

[16] In practice, it is however impossible to reduce the differences between CIF and FOB values to just insurance and transport costs. Numerous other factors will contribute including various definitions of CIF and FOB values used in different countries, see e.g., IMF (2020), as well as measurement and assessment errors and failures, see e.g., OECD (2018).

Table 6.1: TFRI, top 10 (highest risk) and bottom 10 (lowest risk), 2015-2019

	C1<0.30 0.90<C2<1.00	**C1<0.40 1.00<C2<1.10**	**C1<0.50 1.05<C2<1.15**	**C1<0.60 1.10<C2<1.20**	**C1<0.70 1.00<C2<1.20**
Top 10					
1	Gambia	Gambia	Gambia	Gambia	Belize
2	Mauritania	Belize	Belize	Belize	Gambia
3	Belize	Mauritania	Yemen	Yemen	Yemen
4	Yemen	Yemen	Mauritania	Mauritania	Mauritania
5	Guinea	Comoros	Comoros	Comoros	Comoros
6	Comoros	Guinea	Guinea	Guinea	Guinea
7	Bahamas	Sierra Leone	Sierra Leone	Sierra Leone	Sierra Leone
8	Sierra Leone	Bahamas	Bahamas	Bahamas	Myanmar
9	Myanmar	Myanmar	Myanmar	Myanmar	Bahamas
10	Nigeria	Niger	Niger	Benin	Benin
Bottom 10					
10	Hungary	USA	Rep. of Korea	Romania	Rep. of Korea
9	Czechia	Rep. of Korea	Bulgaria	Rep. of Korea	United Kingdom
8	France	United Kingdom	Romania	Japan	Bulgaria
7	Belgium	Romania	United Kingdom	United Kingdom	Romania
6	Romania	Bulgaria	USA	USA	USA
5	United Kingdom	Spain	Spain	Spain	Spain
4	Spain	Turkey	Switzerland	Switzerland	Turkey
3	Switzerland	Switzerland	Turkey	Turkey	Switzerland
2	Italy	Germany	Germany	Italy	Germany
1	Germany	Italy	Italy	Germany	Italy

Source: Authors' calculations based on CEPII, Trade Unit Values.

Only when the ranges are set as low as below 0.30 for component 1, and between 0.90 and 1.00 for component 2, do new countries appear in the ranking that are not otherwise present in the other and higher range categories, see e.g. Nigeria in the top 10 and Czenia in the bottom 10 marked with grey in **Table 6.1**. This means that the TFRI is quite robust concerning the choice of component ranges if the ranges are between 0.30 and 0.70 for component 1 and between 0.90 and 1.20 for component 2. The TFRI for the different range values is further illustrated in **Figure 6.3**-**Figure 6.7** below.

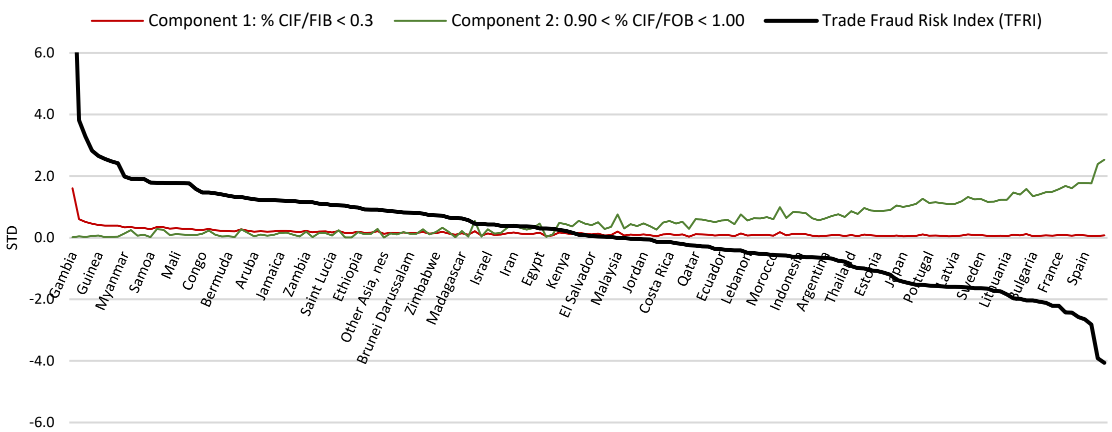


Figure 6.3: TFRI with C1<0.3 and 0.90<C2<1.00, average 2015-2019

Source: QBIS based on CEPII, Trade Unit Values.

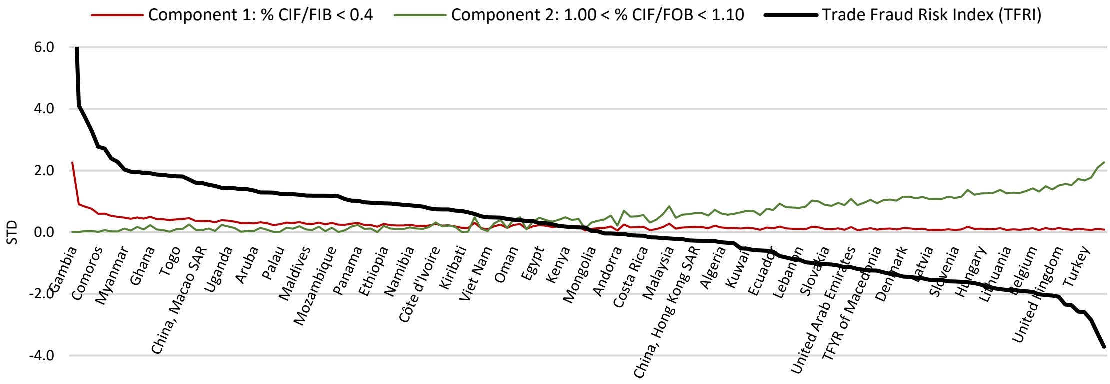


Figure 6.4: TFRI with C1<0.4 and 1.00<C2<1.10, average 2015-2019

Source: QBIS based on CEPII, Trade Unit Values.

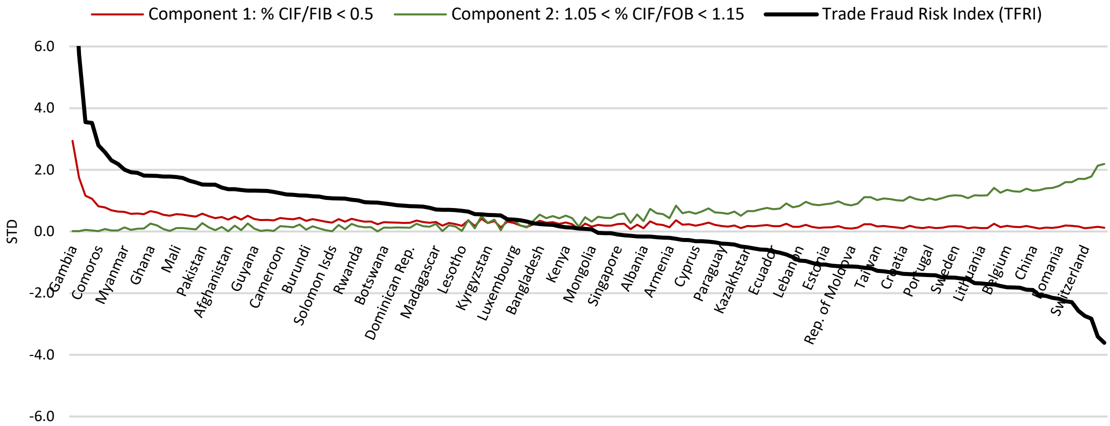


Figure 6.5: TFRI with C1<0.5 and 1.05<C2<1.15, average 2015-2019

Source: QBIS based on CEPII, Trade Unit Values.

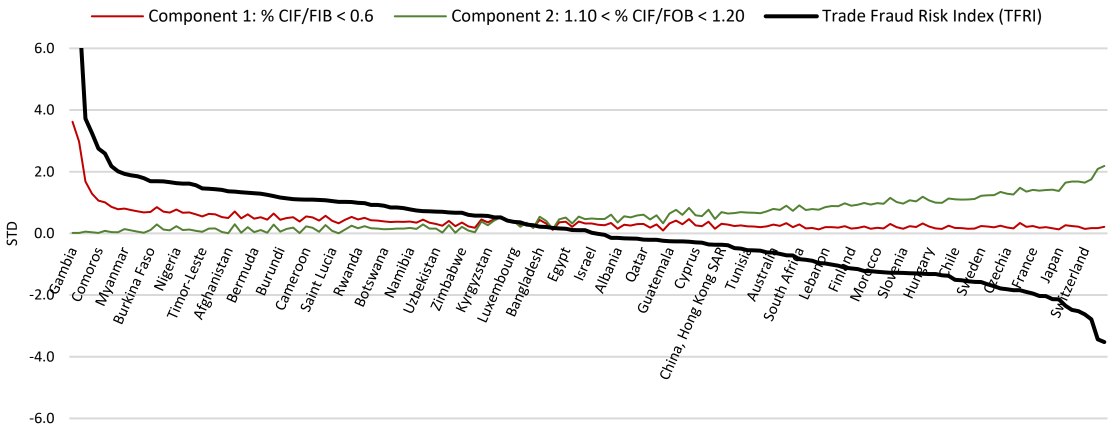


Figure 6.6: TFRI with C1<0.6 and 1.10<C2<1.20, average 2015-2019

Source: QBIS based on CEPII, Trade Unit Values.

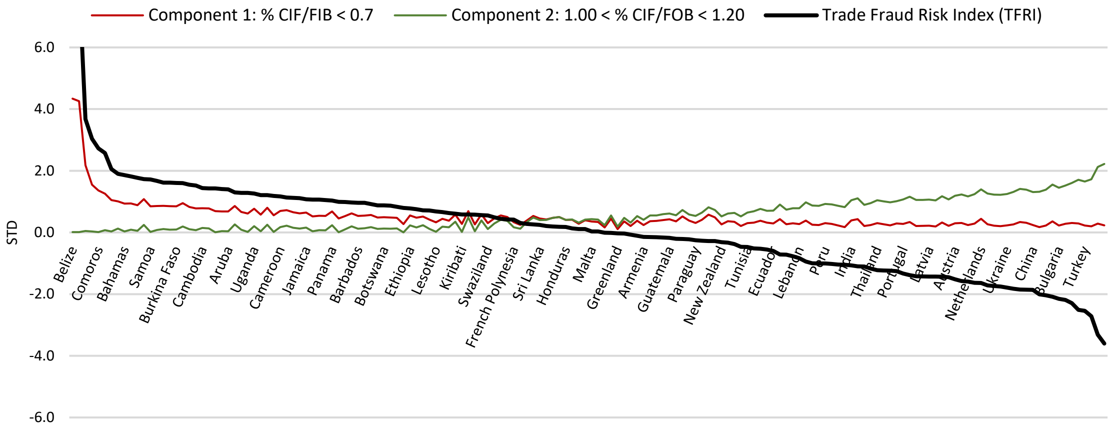


Figure 6.7: TFRI with C1<0.7 and 1.00<C2<1.20, average 2015-2019

Source: QBIS based on CEPII, Trade Unit Values.

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