Identifying trade mis-invoicing through customs data analysis

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Abstract

This paper outlines a methodology for identifying trade transactions where under-valuation or over-valuation is highly suspected. As a first step, the methodology identifies trade transactions with an abnormal unit price. Secondly, it identifies trade transactions with values different from those noted in the records of trading partners. Finally, it presents the trade transactions that were commonly selected from the previous steps. The logic underlying the methodology is that if a trade transaction has an abnormal unit price as well as irreconcilable differences in the trade value ascribed by the trading partner, it would be reasonable to suspect under-valuation or over-valuation in the transaction. In a simulation using actual customs data, this methodology proved effective in detecting fraudulent imports. Of the imports suspected of under-valuation using this methodology, 18 per cent had been penalised and obliged to pay fines, more taxes or duties following customs interventions. This figure is much higher than the share of illicit imports in the test data (4.5%) and the targeting accuracy of the physical inspection of the country (12%). When this methodology was verified using only the imports that had been selected for physical inspection, the targeting accuracy increased to 36 per cent. The result suggests that this methodology could contribute to enhancing the targeting accuracy of existing Customs risk management tools.

1. Introduction

Traditionally, customs administrations are mandated to secure customs duties and taxes, and protect against the under-valuation of imports. However, typologies of trade-based money laundering (FATF/OECD, 2006; APG, 1012; WCO, 2013) and research of illicit financial flows (GFI, 2008–2017; AUC/ECA, 2015; UNCTAD, 2016) hinted at an emerging risk of over-valuation as well as under-valuation with regard to import and export declarations, which have been exploited for cross-border financial flows. The World Customs Organization's (WCO) typology of such illicit financial flows via fraudulent customs declarations is outlined as follows:

- over-valuation of imports intended to disguise capital flight as a form of trade payment
- under-valuation of exports intended to conceal trade profit abroad, i.e. tax havens
- over-valuation of exports or under-valuation of imports intended to incorporate illicit proceeds into domestic financial accounts.

Following this research, the WCO (2018a) recommended that customs administrations endeavour to secure sufficient mandate and resources to combat both over – and under-valuation in export and import declarations alike.

This paper[1] aims to investigate the potential offered by customs data analysis in identifying over- or under-valuation, by using the import data of 'country A' for a one-year period (2016). First, it employs the Price Filter Method[2] (Cathey, Hong & Pak, 2014; De Boyrie, Pak & Zdanowicz, 2005; Hong & Pak, 2016; McNair & Hogg, 2009; Pak & Zdanowicz, 1994) to identify trade transactions with an abnormal unit price. Second, it employs the Partner Country Method[3] (Arenas, Cantens & Raballand, 2012; Berger & Nisch, 2008; Cantens, 2015; Carrère & Grigoriou, 2014; Kar & Spanjers, 2015; Kellenberg & Lenvinson, 2016) to identify trade transactions with values different from those noted in the records of trading partners (mirror trade data). Finally, it presents the list of trade transactions most commonly identified from the previous steps. The logic underlying the methodology is that if a trade transaction has an abnormal unit price as well as irreconcilable differences in the trade value ascribed by the trading partner, it would be reasonable to suspect under-valuation or over-valuation in the transaction.

The main advantage of this methodology is that it can be easily replicated by any customs administration using its own customs data. It can also serve as a benchmark for further research on customs audits, investigations or collaborations with other enforcement agencies. It is important to note that abnormal unit prices and differences in trade records between trading partners are not inherently suspect and may, in fact, be legitimate. High-end goods may have a higher unit price than low-end goods; the price of smartphones online ranges from 100 to 800 euro, depending on their technical specifications. Legitimate reasons for discrepancies in trade records include: the cost, insurance and freight (CIF) and free on board (FOB) ratio; differences between trade partners with regard to classification in the Harmonized System; attribution of trade partners; foreign exchange rates; timing and low-value thresholds. Consequently, this method should only be used as a risk analysis tool, and any suspicious transactions should be examined further in order to draw a reliable conclusion.

2. Data structure

Using the Price Filter Method (PFM), this paper used the most disaggregated (transaction level) import data of country A for one year (2016), composed of 2 million import declarations. The import data provided for the author contains eight fields:

1. anonymised trade identification number

2. date

3. export country

4. distance from the export country

5. HS11 code

6. trade value (USD)

7. quantity

8. weight.

Using the Partner Country Method (PCM), this paper employed two datasets. The first dataset contains import data of country A, as used in the PFM (first column, Table 1), which has three fields: export country, HS11 code and trade value (USD). The second dataset is composed of mirror data of the first dataset; that is, the export data of trading partners to country A (third column, Table 1) sourced from the United Nations Trade Statistics Database (UNCOMTRADE). The mirror trade data also contains of three fields: export country, HS6 code and trade value (USD). As the mirror trade data is not transaction level but aggregated data assessed according to partner-HS6 pairs, the import data of country A was aggregated from transaction level into partner-HS6 level (second column, Table 1) to improve the

comparability of the two datasets. During this process, the data size was reduced from two million to 54,000. The aggregated import data and its mirror data were then combined (fourth column, Table 1), which contains four fields: export country, HS6 code, trade value reported by country A (importer's value) and trade value reported by export country (exporter's value).

It may occur to the reader that the author could have used the import data of country A, sourced from UNCOMTRADE, thus ensuring that the aggregated import data would be matched with its mirror data and simplifying the entire process. The simple explanation for not doing so is that country A had not yet reported its 2016 import data to UNCOMTRADE during the period when this paper was being researched. Additionally, there was a concern over the accuracy of the trade data as reported to the United Nations system; discrepancies have been known to occur on account of political necessity or a desire for trade secrecy.

'Orphan imports' and 'lost exports'[4], as defined by Carrere and Grigoriou (2014), were excluded from the merged data, and only the matching trade data (fifth column of Table 1)—where the value of the importers and exporters was greater than zero—was used in the PCM analysis. This was to avoid over-identification of under- or over- valuation, which can occur because of omissions in trade reporting by countries. Once this process was completed, a significant amount of data was lost; 62,000 to be precise for a final figure of 27,000.

Table 1. Data matching process in partner country method

	① Country A's imports from partners	② Country A's imports from partners	③ Partners' exports to country A	④ Merged	⑤ Matched
Data aggregation	Transaction level	Partner-HS6 level	Partner-HS6 level	Partner-HS6 level	Partner-HS6 level
Data source	Country A	Aggregated from ①	COMTRADE	Merge of ② & ③	Selected from ④
# of data (thousand)	1,965	54	36	62	27
# of partners	179	179	113	183	97

3. First step: price filter method (unit price analysis)

3.1 Overview

During the PFM process, all the imports of country A were divided into 9,086 homogeneous product groups according to their HS 11-digit codes. Subsequently, a **normal unit price range** for each homogeneous product group was set. Any imports with a unit price outside the respective normal unit price range were classified as under- or over-valuation, as the abnormality in unit price could arise from deliberate over- or under-valuation.

3.2 Homogeneous product groups

In this research, the homogeneous product groups were constructed in two different ways. First, this paper replicated the method that appears most frequently in the existing literature (Cathey, Hong, & Pak, 2014; De Boyrie, Pak, & Zdanowicz, 2005; McNair & Hogg, 2009; Pak & Zdanowicz, 1994).[5] This method consists of categorising all trading goods into homogeneous groups according to their HS codes at the most disaggregated level. As the classification of HS codes are regularly reviewed and updated by international and national experts of Customs and trade communities, this method can be perceived as reliable and convenient. As a result, 1.9 million imports were classified into 9,086 homogeneous product groups. The second way for constructing homogeneous groups will be presented in section 7.

3.3 Normal unit price range

Defining a normal unit price range is also an arbitrary process. The literature typically sets a normal unit price range based on the statistical distribution of unit prices of the homogeneous products. Unit prices outside the range are classified as over- or under-valued. This paper[6] used the interquartile methodology: imports with unit prices under the 25th percentile (lower bound) were classified as under-valued imports, and those having unit prices over the 75th percentile (upper bound) were classified as over-valued imports. Figure 1 presents an overview of the construction of homogeneous product groups, and how under-valued or over-valued imports were identified within each group.

Figure 1. Overview of constructing homogeneous product groups and identifying under-/over-valued imports
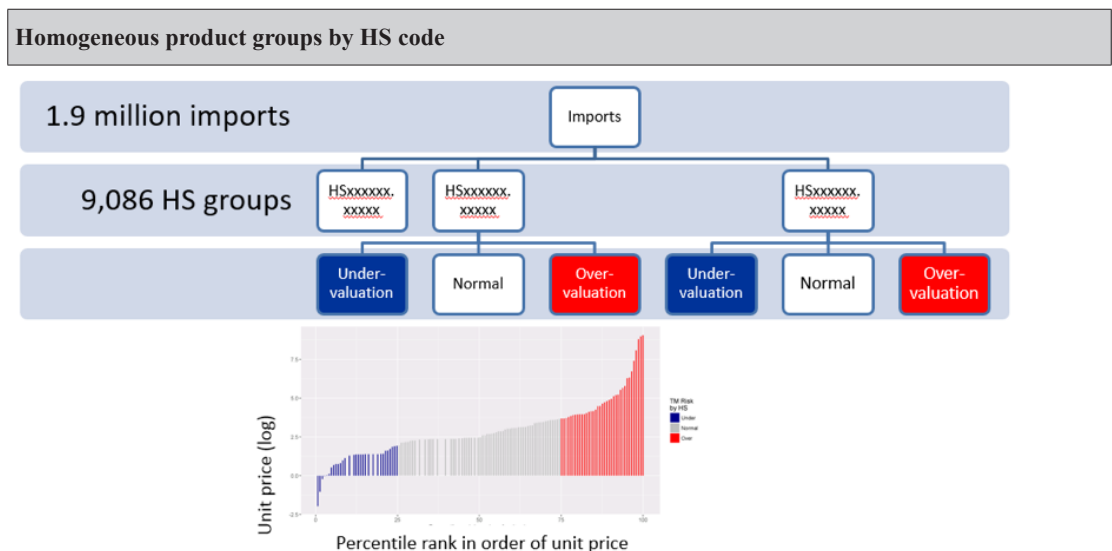
For each over- or under-valued import, the magnitude of over- or under-valuation was estimated as follows:

- over-valuation = (unit price – upper bound) X quantity
- under-valuation = (lower bound – unit price) X quantity.

4. Second step: partner country method (mirror data analysis)
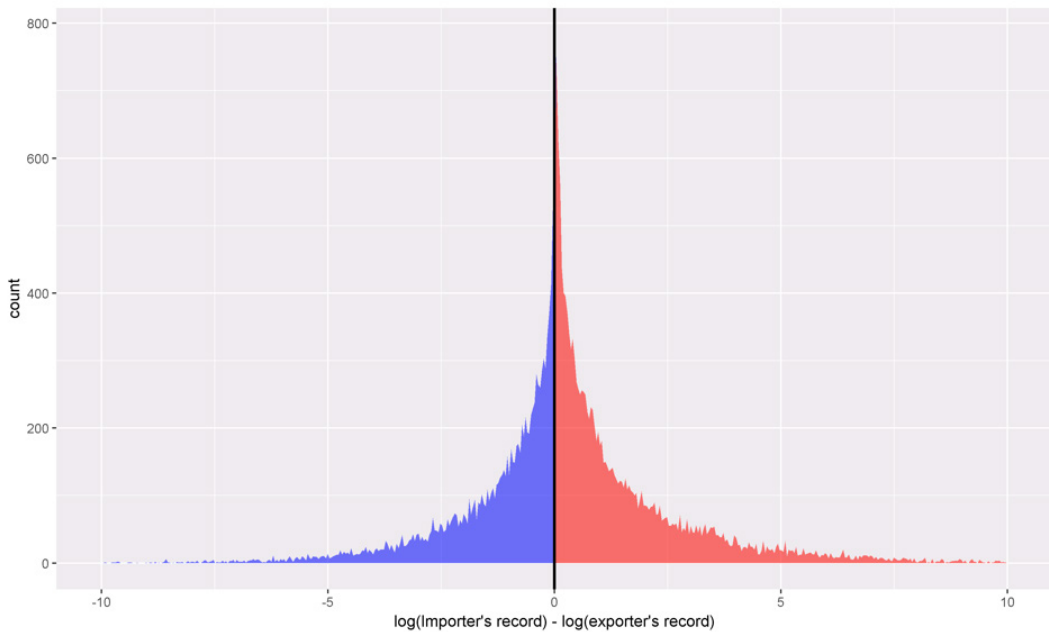
4.1 Overview

Every trade transaction has two records, one recorded by an importing country (importer's value) and the other recorded by an exporting country (exporter's value). While there are several legitimate or statistical reasons that may explain any gap between two trade records, if the gap is significantly large, it would be reasonable to suspect over- or under-valuation in the trade records, and to examine the reasons behind such abnormal discrepancy.

Due to concerns surrounding the confidentiality of trade data, it is unusual to obtain partner countries' trade records at the transaction level. As an alternative, literature focused on PCM employed an aggregated trade data by partner-HS6 level, sourced from UNCOMTRADE. While the aggregation process may offset the magnitude of under- and over-valuation, the literature (Berger & Nisch, 2008; Carrere & Grigorious, 2014; Fisman & Wei, 2004; Gara, Giammatteo & Tosti, 2018; Kellenberg & Levinson, 2016) evidenced the correlation between trade gaps and the attributes of trade transactions such as tariff rate and corruption of trading countries, suggesting that PCM at the partner-HS6 level is still useful and informative in assessing the risk of trade mis-invoicing.

4.2 Classification of over- and under-valuation

According to differences observed in the importer's value and exporter's value, all the partner-HS6 pairs were classified as either over- or under-valuation. A partner-HS6 pair in which the importer's value is larger than the matched exporter's value was classified as an over-valued import, and the size of over-valuation was estimated as the importer's value less the exporter's value. Likewise, a partner-HS6 pair in which the importer's value is less than the matched exporter's value was classified as an under-valued import, and the magnitude of under-valuation was estimated as the exporter's value less importer's value. As Figure 2 presents, among some 27,000 imports at the partner-HS6 level, 12,000 (blue area) were classified as under-valuation and 15,000 (red area) were classified as over-valuation.

Figure 2. Distribution of trade gaps (importer's record – exporter's record) in the import data of country A (2016)

5. Final step: cross-reference PFM and PCM

5.1 Overview

As a final step, this paper identified the imports that were classified into under-valuation both in the first (PFM) and second (PCM) steps. These imports can be presumed to be highly suspicious, regardless of the limitations arising from assumptions and inferential techniques associated with the two methods. The final list of over-valued imports was constructed in a similar fashion. These lists of highly suspicious imports are the final output of this methodology.

5.2 Adjustment of data level

During the final stages of research, an issue of data-level adjustment arose again. While the first step, PFM, produced a list of suspicious imports at the transaction level (List A), the second, PCM, produced a list of suspicious imports at the partner-HS6 level (List B). This paper identified the intersection of the two lists as follows:

1. From the suspicious imports identified by PCM (List B), it extracted only the list of partner-HS6 pairs (List C).

2. From the suspicious imports identified by PFM (List A), only the imports partner-HS6 pairs of which belong to the list C were included in the final list.

As Table 2 shows, 35,000 imports were classified as under-valuation both by PFM and PCM, and 92,000 imports were classified as over-valuation.

Table 2. Cross-reference of PFM and PCM

(# of imports, unit: thousand)					
Under-valuation		PFM			Total
		Normal	Over-valuation		
PCM	Under-valuation	35	330	21	386
	Over-valuation	113	1,074	92	1,279
	Not matched	28	233	28	288
Total		176	1,636	141	1,953

The final list featuring imports where over- or under-valuation is highly suspected contains the following variables:

- transaction identifiable number/code

- (PFM output) unit price, lower-bound and upper-bound of the homogeneous product group, estimates of over- or under-valuation, rank in descending order of over- or under-valuation

- (PCM output) partner-HS6 pair, importer's record, exporter's record, estimates of over- or under-valuation, rank in descending order of over- or under-valuation.

6. Verification

This paper evaluated the effectiveness of the methodology by examining whether the imports it identified as suspicious were actually illicit. The results from this verification stage were positive.

6.1 Actually illicit?

In the verification process, each import transaction was given a new variable (otherwise known as 'actually illicit') which was attributed a value of 1 if the import had been selected by Customs for further inspection, and had been obliged to pay fines or forced to pay more tax or customs duties after the intervention; otherwise the value attributed to the import transaction was 0.

6.2 Targeting accuracy

In a simulation that aimed to detect fraudulent imports with customs data, the targeting accuracy of the methodology was 18 per cent. To put it another way, of the imports suspected of under-valuation by this methodology, 18 per cent had been penalised and obliged to pay more taxes or duties following interventions by Customs. This figure is much higher than the average ratio of 'actually illicit' imports in the test data (4.5%) and the targeting accuracy of physical inspections (red-channel[7]) of the customs administration (12%).

This methodology becomes more powerful when complemented by an existing risk management tool. When this methodology was evaluated using only the imports the customs administration had selected for physical inspection (red-channel), the targeting accuracy increased to 36 per cent. In essence, of the imports classified into the red-channel and suspected of under-valuation by this methodology, 36 per cent had been penalised and obliged to pay more taxes or duties following Customs interventions. Table 3 illustrates the size of the targets and targeting accuracy of each targeting methodology.

Table 3. Targeting accuracy of cross-referencing PCM and PFM (without clustering)

Risk area	Targeting methodology	Inspection[8] (cases)	Inspection rate %	Actually illicit (cases)	Targeting accuracy %
Unknown	Red-channel	532,127	27	66,463	12
Under-valuation	PFM & PCM	34,975	2	6,412	18
	PFM & PCM in Red-channel	16,462	1	5,963	36
Over-valuation	PFM & PCM	92,232	5	1,287	1
	PFM & PCM in Red-channel	12,421	1	586	5

Note: The share of actually illicit in the total imports is 4.5% (= 88000/1900000).

Conversely, among the imports suspected of over-valuation by this methodology, only 1 per cent were found to have been illicit. This may not mean that this methodology is invalid in targeting over-valuation, but rather that the risk of over-valued imports had not been properly evaluated at the borders by the customs administration, resulting in few, if any, seizures of over-valued imports. It is noteworthy that the number of the transactions suspected of over-valuation by this methodology (92,232) is three times as many as that of the transactions suspected of under-valuation. Given that this methodology has proven effective in targeting under-valued transactions, further research and Customs interventions regarding the risk of over-valuation need to be enhanced.

Figure 3 outlines how suspicious imports were identified using a step-by-step process and a sample of 2,875 imports under HS 540752.xxxxx. All the imports were listed in order of unit prices, and the height of each bar represents its unit price (logged value). Imports suspected of under-valuation were marked in blue; imports suspected of over-valuation in red; and actual illicit imports in black.

Figure 3. Process of identifying suspicious transactions and verification (Example of HS 540752. xxxxx; 2,875 imports)
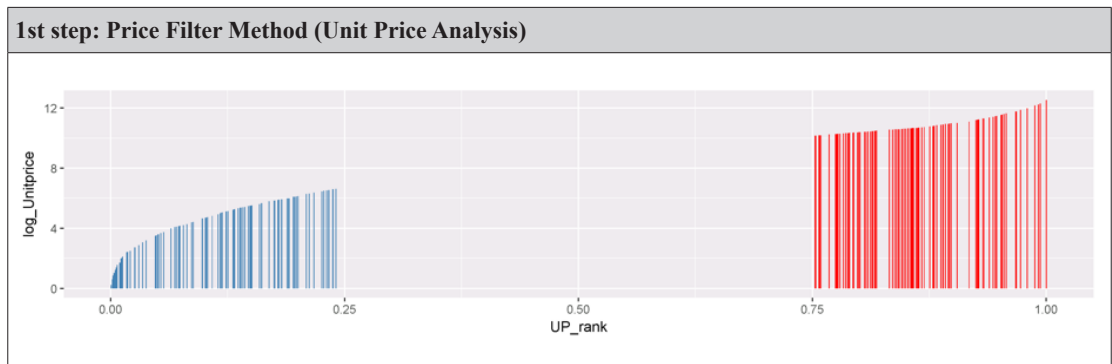
2nd step: PCM
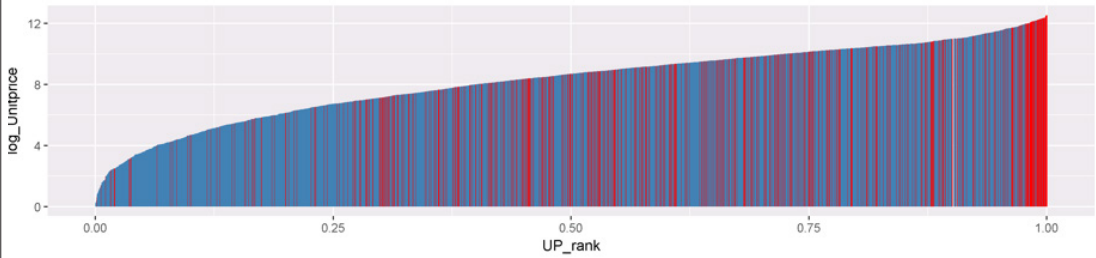
3rd step: Cross-reference PFM and PCM
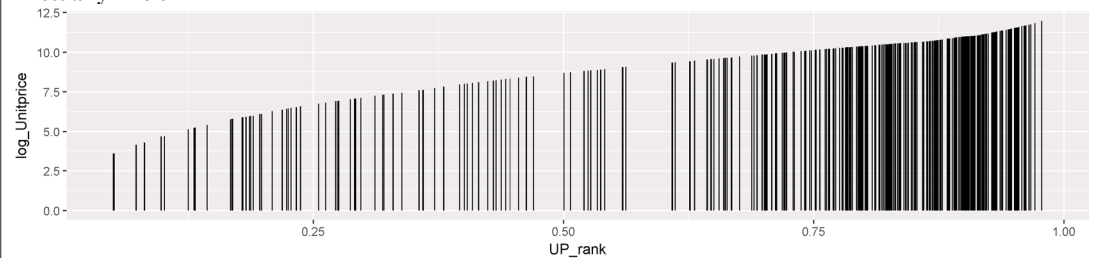

4th step: Verification
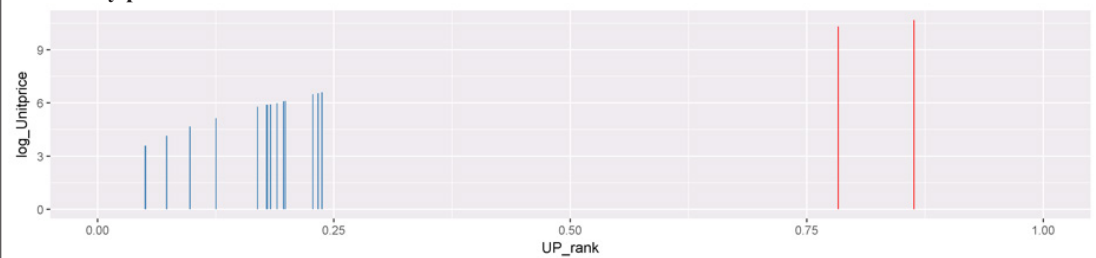
<Actually illicit>

<Correctly predicted under- and over-valuation>
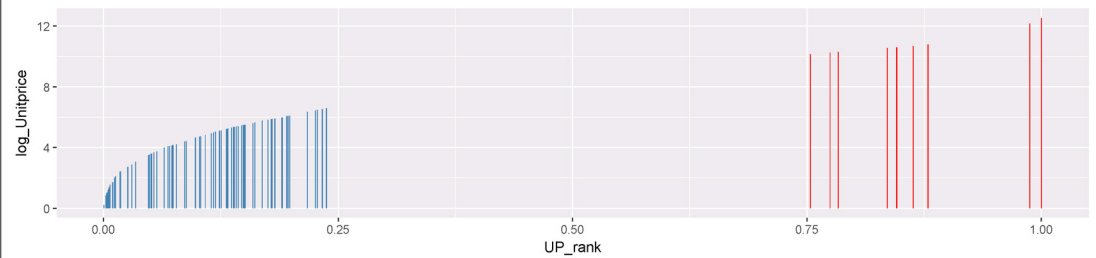
Note:
2,875 imports under HS 540752.xxxxx were listed in order of their quantity-unit prices.
Blue: Under-valuation, Red: Over-valuation, Black: Actually illicit.

7. Another method of constructing homogeneous product groups: clustering

7.1 Clustering

Even goods that share the same HS code can be heterogeneous. Pak and Hong (2018) observed that constructing homogeneous product groups based on HS codes could result in excessively false identification of over-valuation in very high-end goods and under-valuation in very low-end goods and fail to identify abnormal pricing of mid-quality goods.

Therefore, as an alternative to constructing homogeneous product groups in PFM, this paper divided each HS code group further into three clusters in a way that maximises the homogeneity of goods within the clusters and the dissimilarity between clusters. The number of clusters were arbitrarily determined, assuming that there could be high-priced, mid-priced and low-priced goods. With regard to clustering, the author used 'K-means'[9] in R, and three attributes of transactions—unit price, price per weight and distance from partner country—were considered as the clustering factors. Table 4 outlines the rationale of those attributes.

Table 4. Attributes of trade transactions to be considered

Attributes	Rationale
Unit price	High-end goods are likely to have a higher unit price. Likewise, low-end goods are likely to have a lower unit price for legitimate reasons.
Price per weight	Difference in raw materials may legitimately affect the price. For example, a gold ring has a higher price per weight than a silver ring.
Distance from partner country	An importer's value includes the cost of insurance and freight, which are partly proportional to the distance of transportation from the export country to the import country. Therefore, import goods originating from distant countries are likely to incur a higher transportation cost, and consequently and legitimately, a higher unit price, than those from a neighbouring country.

All other processes in the second (PCM) and final step (cross-reference PFM and PCM) were identical to the previous one. In this methodology, 9,082[10] HS groups were further categorised into 27,246 homogeneous product groups according to the attributes of imports: unit price, price per weight and distance from the origin country. Figures 4 and 5 present an overview of homogeneous product groups and three examples of clustering imports under the same HS11 codes into more homogeneous product groups.

Figure 4. Overview of constructing homogeneous product groups by clustering
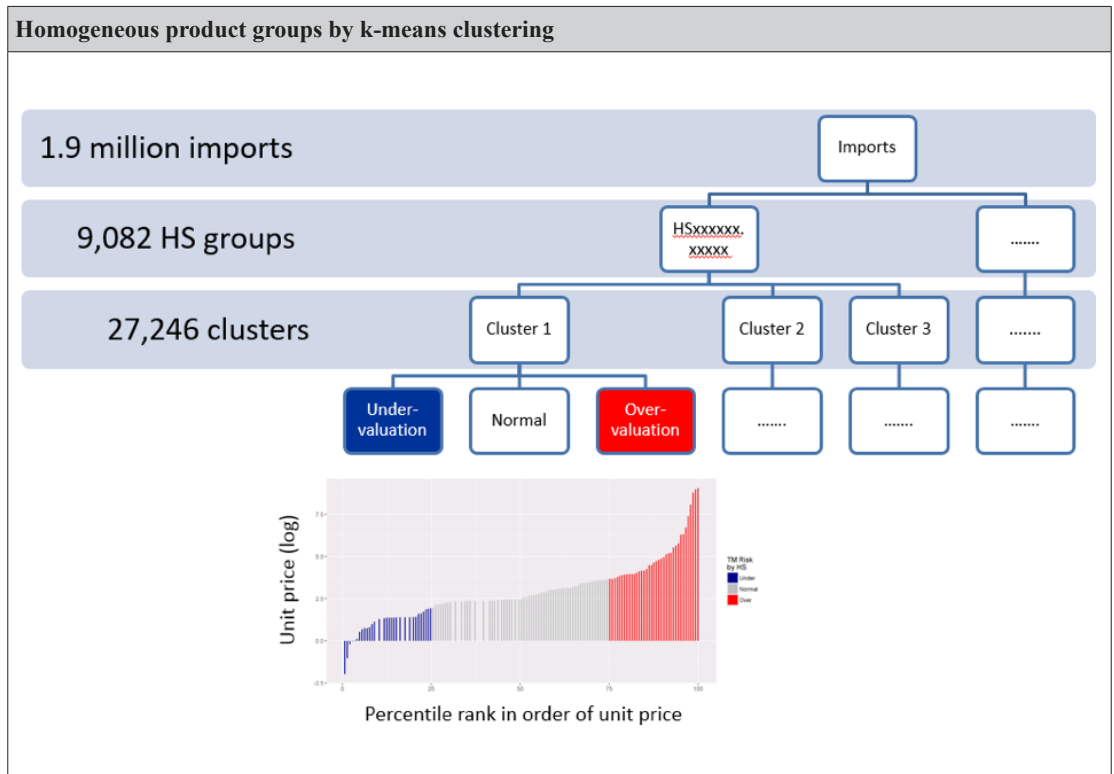
Figure 5. Examples of the formation of homogeneous product groups

A. Product: HS520942.xxxxx (woven cotton fabrics, denim…)

Cluster	Size (number of imports)	Cluster center		
		Unit price (log)	Weight price (log)	Distance (log)
1 (light green)	2,434	3.3	1.7	7.5
2 (dark green)	3,978	7.3	3.3	7.3
3 (blue)	5,883	10.5	3.2	7.3
Total	12,295	–	–	–

B. Product: HS980400.xxxxx (furniture…)

Cluster	Size (number of imports)	Cluster center		
		Unit price (log)	Weight price (log)	Distance (log)
1 (light green)	4,337	9.4	4.3	7.4
2 (dark green)	11,063	11.0	2.1	7.5
3 (blue)	22,701	12.7	3.6	7.1
Total	38,101	–	–	–

C. Product: HS860900.xxxxx (Container specially designed or equipped for…)

Cluster	Size (number of imports)	Cluster center		
		Unit price (log)	Weight price (log)	Distance (log)
1 (light green)	34,335	6.9	−1.4	7.2
2 (dark green)	18,489	7.2	−1.1	8.9
3 (blue)	22,361	8.7	−0.1	7.8
Total	75,185	–	–	–

7.2 Verification of clustering

When 27,246 homogeneous product groups were constructed based on the k-means clustering in the first step (PFM), the number of targets suspected of under-valuation decreased from 34,975 to 26,924, and the targeting accuracy of the methodology was also reduced from 18 per cent to 16 per cent. Table 5 illustrates the size of the targets and targeting accuracy with a clustering approach, which is comparable to Table 3.

Table 5. Targeting accuracy of cross-referencing PCM and PFM (with clustering)
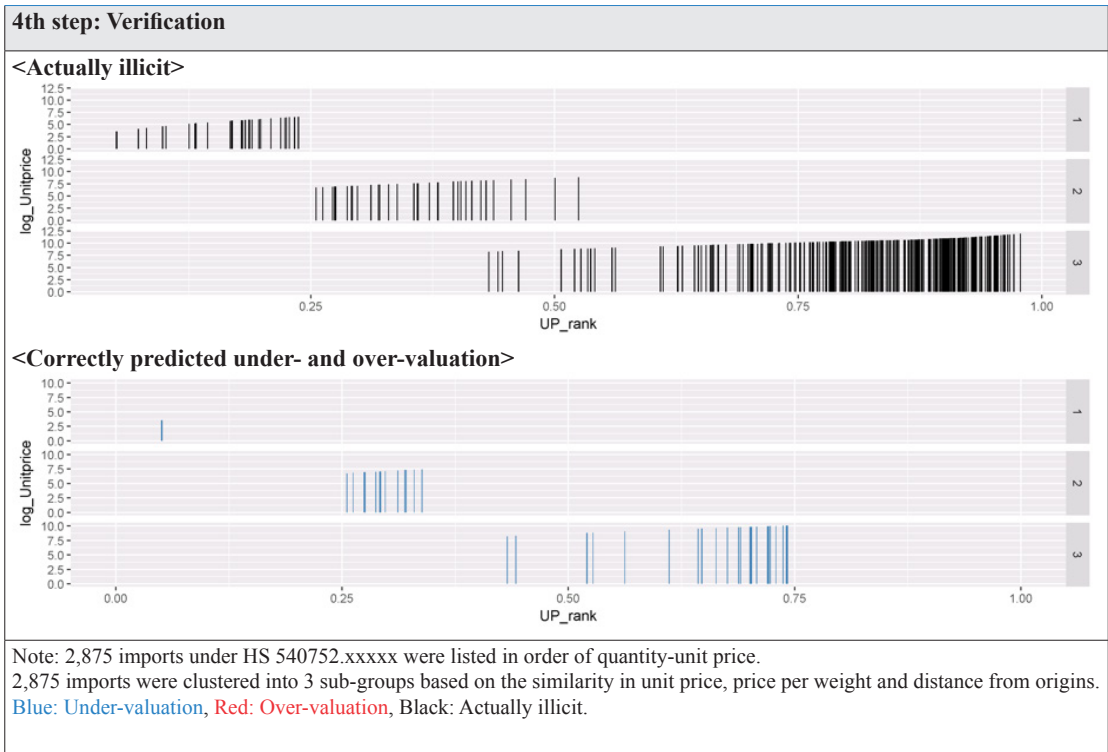
Risk area	Targeting methodology	Inspection (cases)	Inspection rate %	Actually illicit (cases)	Targeting accuracy %
Overall	Red-channel	532,127	27	66,463	12
Under-valuation	PFM & PCM	26,924	1	4,337	16
	PFM & PCM in Red-channel	12,018	0.6	3,896	32
Over-valuation	PFM & PCM	88,517	5	1,866	2
	PFM & PCM in Red-channel	19,388	1	977	5
Note: The share of actually illicit in the total imports is 4.5% (=88000/1900000).					

This result may arise from the fact that the number of clusters and the attributes for clustering were arbitrarily and uniformly determined across 9,082 HS codes, and consequently failed to capture under-valued or over-valued imports in some HS codes. The methodology accompanied by a clustering approach performed better in detecting actual illicit imports in only 469 HS groups than the methodology used without a clustering approach. Figure 6 presents an overview of this methodology with clustering using the same sample of Figure 3 (2,875 imports under HS 540752.xxxxx), where the clustering approach detected more actual illicit imports than the non-clustering approach.

Figure 6. Process of identifying suspicious transactions and verification with clustering (Example of HS 540752.xxxxx)

4th step: Verification
<Actually illicit>
<Correctly predicted under- and over-valuation>
Note: 2,875 imports under HS 540752.xxxxx were listed in order of quantity-unit price. 2,875 imports were clustered into 3 sub-groups based on the similarity in unit price, price per weight and distance from origins. Blue: Under-valuation, Red: Over-valuation, Black: Actually illicit.

In future iterations of this research, clustering techniques could be customised in accordance with features of each HS code. With regard to the examples of clustering in Figure 5, if country A imports product HS520942.xxxxx only from one country, the distance should not be included as an attribute for constructing clusters.

8. Conclusion

This paper identified imports with an abnormal unit price as well as with trade values different from those in the records of trading partners and verified that such imports have a higher risk of under- or over-valuation. The main strength of this method is that it can be replicated by any customs administration using its own trade data. Owing to the prevalence of electronic customs declarations[11] and the availability of open source big data analysis tools, this method is gaining traction and becoming more appealing, even to developing countries.

However, the trade transactions identified using this methodology may have legitimate reasons for their abnormal unit prices and irreconcilable mirror trade data. In addition, the final result of this methodology (i.e. the list of suspicious trade transactions) is heavily reliant on the assumptions and inferential techniques of the analysis. For example, whether 'orphan imports' and 'lost exports' are included in the analysis may impact the overall result. Therefore, this method should be used only as a way to assess the risk of over- and under-valuation in combination with other commonly used risk indicators such as the legal compliance of traders.

Nevertheless, this methodology could be a good starting point for Customs to establish which transactions, products, traders or origins have a higher risk of under- or over-valuation. Further product-specific or region-specific research could be continued.

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Notes

1   The paper is a continuation of the WCO study report on IFFs/TM (2018), chapter 7 with different sets of data.

2   PFM is also called 'unit price analysis'. For details of this method, refer to the WCO study report on IFFs/TM (2018), chapter 4.

3   PCM is also called 'mirror data analysis'. For details of this method, refer to the WCO study report on IFFs/TM (2018), chapter 3.

4   Carrere and Grigoriou (2014) defined an 'orphan import' as a case where there is no corresponding record on the exporter's side, and a 'lost export' as a case where there is no corresponding record on the importer's side.

5   For details, refer to the WCO study report on IFFs/TM (2018), chapter 4.

6   Each import data in this research has two measurement units: quantity and weight. For a conservative identification of suspicious transactions, imports both quantity-unit price and weight-unit price of which are outside respective normal unit price ranges were classified as under- or over-valued imports.

7   The customs administration of country A had classified all their imports into a 'Green (low-risk)', 'Yellow (medium-risk)' or 'Red (high-risk)' channel according to their risk analysis and conducted physical inspections to the red-channel goods.

8   In the 'Red-channel' methodology (first row), the number of 'Inspection' represents that of actual inspections, whereas in the 'PFM & PCM' and 'PFM & PCM in Red-channel' methodologies, the numbers of 'Inspection' represent those of imports predicted as illicit by the methodologies.

9   For further details, refer to https://cran.r-project.org/web/packages/ClusterR/ClusterR.pdf

10 Trade transactions under the HS11 codes with less than 4 transactions were excluded. The number of 4 was arrived at after considering that each HS11 group will be divided into three clusters, and that each cluster should have at least 1 transaction, which is arbitrary. After these criteria were applied, the size of the data decreased by 22, and the number of HS groups decreased by 4.

11 According to the WCO annual report 2017–2018, around 90 per cent of import and export declarations were submitted to customs electronically.

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