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World Customs Journal

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Editorial

I commented in the last edition of the Journal that, despite being only two weeks away from the proclaimed date of the UK's departure from the EU, no resolution was in sight. With that 'deadline' having come and gone, and another 'deadline' looming, the outcome is as uncertain as ever.

Such uncertainty presents a serious threat to the prosperity of the UK trading community, given that the percentage of overseas consignments that is subject to customs requirements could increase from 25 to 100 per cent with little or no notice. In the circumstances, a good understanding of customs processes is key to business success.

A silver lining in the Brexit cloud has been the effort made by Her Majesty's Revenue and Customs (HMRC) to strengthen the capacity of the customs profession throughout the UK in preparation for what can only be described as a new era of international trade. To achieve this, HMRC has not only supported the development of a customs academy for the private sector, but is also fully subsidising those who wish to enrol in its courses. This degree of government support for a country's international trading community is unprecedented and is something for which the administration should be commended.

Turning to the current edition of the Journal, the Editorial Board is pleased to include a section dedicated to papers based on a series of innovative WCO workshops on data analytics. This emerging area of research is focused on the need to better utilise the huge amount of information that is available to customs administrations in order to inform strategic and operational decision-making. The potential benefit of developing increasingly sophisticated analytics is obvious, and we would encourage further contributions in this relatively embryonic research field.

Finally, it is with pleasure that I announce the decision to dedicate the September 2020 edition of the Journal to papers that will be delivered at next year's WCO PICARD conference, further details of which are provided in this edition's special report. The Editorial Board looks forward to working closely with the WCO on this initiative and welcomes proposals from prospective contributors.

David Widdowson
Editor-in-Chief

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Section 1

Academic Contributions

The impact and countermeasures of new tax policy for cross-border e-commerce in China[1]

Bowen Shi, Xiang Gao, Liangting Jia, Xiangnan Guo

Abstract

The implementation of the *Announcement on Issues concerning the Regulation of Retail Import and Export Commodities through Cross-Border E-commerce* marked the end of a tax-free era of cross-border e-commerce in China. The new policies (known in this paper as the New Deal) have had a profound effect on enterprises, consumers and overseas purchasing agents engaged in cross-border e-commerce transactions. Empirical data from eight cross-border e-commerce pilot cities (Shanghai, Chongqing, Guangzhou, Shenzhen, Zhengzhou, Ningbo, Hangzhou and Dongguan) were studied. Results from the research into these pilot cities show that: (1) the development of cross-border e-commerce among those cities is unbalanced; (2) the New Deal has not resulted in a significant impact on import and export behaviours; and (3) the tax burden of cross-border e-commerce enterprises has increased considerably since the implementation of the New Deal.

Based on these results, for the purpose of promoting the development of cross-border e-commerce, the following recommendations are made: (1) improve the policies and regulations to create an environment that supports e-commerce development; (2) facilitate the port cooperation mechanism and promote the construction of a customs single window; (3) strengthen top-level design and improve the coordination and management between relevant authorities; and (4) encourage enterprises to follow market trends and focus on product innovation and market expansion.

1. Introduction

With economic development and mature internet technology, cross-border e-commerce has established itself as rapidly developing commercial mode (Saimiee, 1998). In academia, the generally accepted definition of cross-border e-commerce is the trade in goods between parties from different countries or regions, and related business data exchange through the internet and its relevant information platforms (Pan, Gunasekaran & McGaughey, 2006; Lee, 2012). In this paper, cross-border e-commerce refers to a commercial offering of goods and related service transactions by which trading parties from different customs territories conclude transactions and settle payment by means of platforms such as e-commerce, logistics and payment platforms linked to China Customs, and goods delivery through cross-border logistics.

On 24 March 2016, the Ministry of Finance, General Administration of Customs of China and China's State Administration of Taxation jointly issued the *Notice on Cross-Border E-commerce Retail Import Taxation Policy* (Cai Guan Shui [2016] No.18), which substantially modified the import tax on cross-border retail transactions (Ministry of Finance, 2016). At the same time, a dozen administrations,

including the General Administration of Customs of China and the Ministry of Finance, released the first and second wave of the 'positive lists' of cross-border retail import goods on 7 April and 15 April, respectively.

These lists were introduced to further standardise cross-border retail import processes.

Through this series of policies, cross-border e-commerce has undergone drastic changes in the revenue collection and supervision environment (Xiang & Liangting, 2016). The policies have also signified the end of the tax-free era of cross-border e-commerce, which has a profound influence on enterprises, consumers and overseas purchasing agents engaged in cross-border e-commerce transactions.

The New Deal—which in this paper refers to the series of policies on tax and supervision of cross-border e-commerce that came into effect after 8 April 2016—introduced changes to the regulation of cross-border e-commerce, making the tax framework much clearer and introducing tax equality. However, because the introduction of the New Deal did not include a sufficient buffer period, e-commerce enterprises were too late to modify their information systems, which increased the burden on those enterprises because goods that were destined for bonded warehouses could not be processed before those policies come into practice. Furthermore, the positive lists lack an authoritative interpretation, with each side interpreting the lists differently because they lack clarity. It is also argued that the value limits set by the New Deal are too low, as they hinder citizens wishing to purchase high-end cosmetics and other commodities.

In order develop an in-depth knowledge of China's cross-border e-commerce after the New Deal, our group members have undertaken research in the cross-border e-commerce pilot cities of Shanghai, Chongqing, Guangzhou, Shenzhen, Zhengzhou, Ningbo, Hangzhou and Dongguan. Following an empirical analysis of the data gathered, highlighting the differences between before and after the New Deal, we propose a number of cross-border e-commerce initiatives.

2. The change of tax policy before and after the New Deal

2.1 Cross-border e-commerce tax policy before the New Deal

Before the New Deal, tax generated from China's cross-border e-commerce was primarily made up of postal tax or tariffs, value-added tax (VAT) and excise on certain goods.[2] In general, the postal tax was applied to private imports, that is, goods for personal use with a value of no more than 1,000RMB, while tariffs, VAT and excise applied to commercial imports.

The tax rates applying to commercial goods before the New Deal were set at 10 per cent, 20 per cent, 30 per cent and 50 per cent, with such goods attracting a tariff rate, VAT rate and excise rate.

Private imports subject to postal tax were exempted from paying the tax in situations where the tax generated by a single consignment was less than 50RMB. This was advantageous for low-value private imports.

2.2 Cross-border e-commerce tax policy after the New Deal

After the New Deal, the tax exemption policy was no longer generally applicable to private imports, and tariffs, excise and postal tax applied. There were, however, some concessions for lower value goods, provided they met the following criteria:

- for personal and reasonable use (within the positive list)
- within a single purchase value limit of 2,000RMB
- within an annual purchase value limit of 20,000RMB.

For private imports, tariffs are now levied at 0 per cent and VAT and excise duties are levied at 70 per cent, whereas for commercial imports, tariffs, VAT and excise are levied at applicable tariff rates, VAT rates and excise rates.

Following the New Deal, neither private imports nor commercial imports are eligible for the 50RMB tax exemption. In other words, since the New Deal was introduced, all categories of imported goods are taxed.

2.3 Influence on cross-border e-commerce after the New Deal

2.3.1 Increase of cross-border e-commerce tax burden

With the implementation of the new tax policy, cross-border e-commerce policy dividends have disappeared, and the cost of many imported goods has increased. It is estimated that the rate of increase is at least 11.9 per cent. The commodities most affected include low-cost cosmetics, maternal and child products, and luxury products.

Before the New Deal, the tax on cosmetics valued at no more than 100RMB was zero, while after the New Deal was introduced, the tax rate increased to 32.9 per cent. Similarly, before the New Deal, most maternal and child goods were exempt from tax, while after the New Deal, the tax rate is 11.9 per cent. For luxury goods with prices higher than 2,000RMB, the tax rate has remained similar compared to that of traditional importing, but the dutiable value is higher. For example, the tax rate of high-end watches was 30 per cent before the New Deal and 48 per cent after the New Deal, with the retail price being viewed as the dutiable price.

At the same time, the tax burden for certain goods has been reduced, such as cosmetics and electrical products within a certain value range. For example, for cosmetics priced between 100RMB and 2,000RMB, the tax burden has decreased from 50 per cent to 32.9 per cent (see Table 1).

Table 1: Comparison of tax burden of different commodities before and after the New Deal

Commodity Category	Value (RMB)	Before the New Deal		After the New Deal			Change
		Tax rate	Levy	Tariff	VAT	Excise	
Maternal and child	<500	10%	0%	0%	11.9%	0%	↑11.9%
	>500	10%	10%	0%	11.9%	0%	↑1.9%
Cosmetics	<100	50%	0%	0%	11.9%	21%	↑32.9%
	>100	50%	50%	0%	11.9%	21%	↓17.1%
Clothing, electrical equipment	<250	20%	0%	0%	11.9%	0%	↑11.9%
	>250	20%	20%	0%	11.%	0%	↓8.1%
High-end watches	>2000	30%	30%	11%	17%	20%	↑18.0%

2.3.2 Change from the bonded model to direct mail model

The disappearance of the tax-exemption policy means that cross-border e-commerce changed from a bonded model to a direct mail model. Currently, China's cross-border e-commerce retail imports are mainly divided into two business models:

1. Overseas direct mail model. In this model, domestic consumers confirm an order through cross-border e-commerce platforms, the platform sends the order information to overseas suppliers, and the overseas suppliers deliver the commodities to consumers. Cross-border logistics is usually completed by professional cross-border logistics companies.

2. Bonded model. In this model, cross-border e-commerce enterprises will import commodities and goods in a wholesale way from overseas suppliers and store them in a bonded warehouse in one of the pilot cities. When there is an order from consumers, the commodities and goods will be delivered by logistics companies from the bonded warehouse to the consumer.

With the cancellation of tax-exemption policies, the bonded model is affected more greatly than the overseas model. The profits and revenues under the bonded model are more dependent on the so-called 'explosive' goods, which focuses more on quantity than quality. After the New Deal, the collection of tariffs, import VAT and excise—collectively known as the 'comprehensive cross-border e-commerce tax'—replaced the traditional postal tax. Without a tax-exemption policy, there is an increase on costs of cross-border e-commerce retail commodities and goods, which will significantly impact enterprises using the bonded model.

In terms of the overseas direct mail model, however, the adjusted postal tax remains similar as there is still some tax-exemption for goods under a certain value. Even if the majority of commodity prices increases, the impact on the goods imported through overseas direct mail model is much less than that through the bonded model. Therefore, many domestic cross-border e-commerce enterprises will transfer their operation from the bonded model to the overseas direct mail model.

2.3.3 Benefits of new policies

The new policies are conducive to safeguarding the state tax, improving the efficiency of supervision, and promoting fair competition in the e-commerce industry. The New Deal has increased the tax burden of the entire cross-border e-commerce industry, which is designed to safeguard the national fiscal revenue (Cui & Jiang, 2015). The tax exemption for goods under 50RMB has been cancelled, making the ethically 'grey' practice of splitting larger purchases into small parcels to avoid tax is difficult to achieve, largely blocking the original tax loopholes. As there is no longer such a large number of fragmented small parcels, supervision pressures of customs and other departments is eased, reducing regulatory costs and improving clearance speed of cross-border c-commerce commodities and goods.

The New Deal defines the 'trading' attribute of cross-border e-commerce retailers' imports, which is distinguished from the 'goods' that are traditionally subject to postal tax, clarifying the 'exclusive' tax system applicable to retail imports of cross-border e-commerce. The clarification of grey areas in the business helps to avoid unfair competition.

3. Statistical analysis

The impact of the New Deal on the cross-border e-commerce industry has been analysed statistically. For comparison, the study selected the average data from 2015, before the implementation of New Deal, and data after the implementation of New Deal. The year 2015 is considered to be the most significant year of development of cross-border e-commerce business, making the relevant data statistically comparable.

3.1 Changes in average daily customs clearance

The average number of votes before and after the New Deal on the average of the two pairs of sample analysis is performed; the results are shown in Table 2. Through the t-value and t-double-tail critical, we can see that at 5 per cent of the significant level, the cross-border e-commerce daily average clearance votes did not significantly change after the introduction of the New Deal policies. In fact, in some pilot cities, the number of single-day clearances increased. This may be due to the suspension of the implementation of the New Deal on the elimination of cross-border e-commerce business. It can also be seen that the impact of the New Deal on the cross-border e-commerce business is not large.

Table 2: Mean analysis of double samples of average daily customs clearance of cross-border e-commerce before and after New Deal

	Before the New Deal	After the New Deal
Average	190.4024	192.6307
Variance	72990.15	33302.63
Observations	6	6
Poisson correlation coefficient	0.524199	
Assuming an average difference	0	
df	5	
t Stat	–0.02336	
P(T<=t)	0.491134	
T single tail critical	2.015048	
P(T<=t)	0.982269	
T double tail critical	2.570582	

3.2 Changes in average daily taxation

A pair of two samples of the average value of the daily taxation of the New Deal is analysed. The results are shown in Table 3. Through the t-value and t-tail critical, we can see that at the 5 per cent significance level, the average daily taxation of the cross-border e-commerce after the New Deal improved significantly. This statistical result illustrates two issues: the import volume did not significantly decline and the tax burden increased.

Table 3: Mean analysis of double sample of average daily taxation of cross-border e-commerce before and after New Deal

	Before the New Deal	After the New Deal
Average	15.81576	96.90406
Variance	239.6132	2387.971
Observations	7	7
Poisson correlation coefficient	0.660951	
Assuming an average difference	0	
df	6	
t Stat	–5.31773	
P(T<=t)	0.0009	
T single tail critical	1.94318	
P(T<=t)	0.001799	
T double tail critical	2.446912	

3.3 Changes in average tax rate

The average value of tax rate of the New Deal is analysed; the results are shown in Table 4. Through the t-value and t-tail critical, we can see that at 5 per cent of the significance level, the average tax rate of cross-border e-commerce after the New Deal has been significantly improved. This shows that the tax burden of cross-border e-commerce after the New Deal is greater than before.

Table 4: Mean analysis of double samples of average tax rate of cross-border e-commerce before and after the New Deal

	Before the New Deal	After the New Deal
Average	0.02366	0.12332
Variance	0.000327	2.54E–05
Observations	5	5
Poisson correlation coefficient	0.116814	
Assuming an average difference	0	
df	4	
t Stat	–12.246	
P(T<=t)	0.000128	
T single tail critical	2.131847	
P(T<=t)	0.000255	
T double tail critical	2.776445	

3.4 Changes in average daily import volume

A pair of two samples of the average value of the average import and export business volume is performed before and after the New Deal; the results are shown in Table 5. Through the t-value and t-tail critical, we can see that at the 5 per cent significance level, there is no significant change in the average import volume of cross-border e-commerce business.

Table 5: Mean analysis of double samples of average daily import volume of cross-border e-commerce before and after the New Deal

	Before the New Deal	After the New Deal
Average	168.6855	148.771
Variance	64126.51	34265.72
Observations	7	7
Poisson correlation coefficient	0.519063	
Assuming an average difference	0	
df	6	
t Stat	0.236272	
P(T<=t)	0.41054	
T single tail critical	1.94318	
P(T<=t)	0.82108	
T double tail critical	2.446912	

3.5 Changes in the average daily bonded import volume

An analysis of the daily average bonded import volume before and after the New Deal was performed; the results are shown in Table 6. Through the t-value and t-tail critical, it can be seen at 5 per cent of the significance level, cross-border e-commerce daily average bonded import volume has no significant change.

Table 6: Mean analysis of double samples of average daily bonded import volume of cross-border e-commerce before and after the New Deal

	Before the New Deal	After the New Deal
Average	501.7108	558.5253
Variance	183911.3	202472.8
Observations	8	8
Poisson correlation coefficient	0.977705	
Assuming an average difference	0	
Df	7	
t Stat	–1.68913	
P(T<=t)	0.067523	
T single tail critical	1.894579	
P(T<=t)	0.135046	
T double tail critical	2.364624	

3.6 Changes in average daily export volume

A total of two pairs of sample analyses of the average daily export volume of cross-border e-commerce in pilot areas was performed before and after the New Deal. The results are shown in Table 7. Through the t-value and t-tail critical, we can see that at 5 per cent significance level, the average daily export volume of cross-border e-commerce has not changed significantly.

Table 7: Mean analysis of double samples of average daily export volume of cross-border e-commerce before the New Deal

	Before the New Deal	After the New Deal
Average	698.8265	247.606
Variance	579550.6	40258.36
Observations	4	4
Poisson correlation coefficient	0.90747	
Assuming an average difference	0	
df	3	
t Stat	1.541831	
P(T<=t)	0.11039	
T single tail critical	2.353363	
P(T<=t)	0.220779	
T double tail critical	3.182446	

4. Discussion

The development of cross-border e-commerce in different pilot cities is not balanced, because the local government and cross-border e-commerce enterprises have made different strategic layouts and selections according to different customs supervision models (traditional export, special export zone, direct purchase and import, bonded import), while at the same time the parameters of customs supervision and facilitation innovation are also different. That is why there are different priorities and characteristics in the import and export of cross-border e-commerce in the pilot cities, whose respective experiences and lessons are worth learning from.

The impact on import and export of cross-border e-commerce by the New Deal is not that significant. After the New Deal, due to the one-year buffer period for cross-border e-commerce, cross-border e-commerce recovered rapidly. Before and after the New Deal, the average daily import clearance, average daily bonded import volume, and the average daily export volume in these pilot cities did not significantly change; cross-border e-commerce is developing steadily.

After the New Deal, the tax burden of cross-border e-commerce enterprises increased significantly. This is due to the introduction of tariff, VAT and excise on cross-border e-commerce goods, with only limited concessions and no tax-exemption amounts, while there was once a 50RMB tax-exemption amount for postal tax. So, the tax burden has risen remarkably, and the tax revenue of each pilot city has also been significantly increased. This shows that after the New Deal the tax policy and the tax environment has undergone significant changes.

5. Conclusion and recommendations

The original intention of the New Deal was to stimulate domestic consumption, promote fair competition and strengthen the import tax administration. But the New Deal did not allow a long enough transition period and cross-border e-commerce enterprises were too late to modulate their information system, which resulted in an increased tax burden. The positive lists lack the interpretation of authoritive policy, which makes the parties reach different understandings; and the new single purchase limit is too low, which deters citizens from buying some high-end cosmetics and other goods.

Based on our analysis, we make the following suggestions:

5.1 Implement unified cross-border e-commerce management standards to avoid 'policy depression'

There are two factors that led to the unbalanced development of cross-border e-commerce in the eight pilot cities. On one hand, local governments and cross-border e-commerce made different strategic choices in four different customs supervisions: traditional export, special export zone, direct-purchase import and bonded import zone. On the other hand, pilot cities and cross-border e-commerce enterprises had their own management system with different standards. Each pilot city designed a self-contained management pattern of cross-border e-commerce according to the local characteristics. Although it is conducive to local conditions to solve practical problems to some degree, it also affects the effective implementation of the law enforcement of unity and may even cause relative 'lowland' regulation.

The research found that in the B2C cross-border e-commerce, 'three single data' (orders, bills of lading, payment orders) management is different. Some pilot cities require enterprises to send 'three single data' for an automatic verification audit, while other pilot cities do not have the same requirements, so companies only need to provide 'two single' or even 'one single' data. Some pilot cities have strict management policies about splitting a larger order into smaller ones, and strictly monitor the accuracy of the price enterprise offer, while other pilot cities do not manage this behaviour as closely.

According to reports of cross-border e-commerce, the policy gap between pilot cities brought vicious competition in cross-border e-commerce, and may even produce the phenomenon that bad money drives out good. Given that cross-border e-commerce lacks the top-level design (Xiang & Liangting, 2016), it is recommended that the competent authorities study the direction of China's cross-border retail import development, formulate supporting policies for the decisive role of market in resource allocation, know the medium- and long-term policy guidance on cross-border retail import and improve the top-level design of cross-border e-commerce, so as to guide the overall situation, to coordinate cross-border e-commerce to become a policy of highland. The introduction of relevant operational procedures and implementation guidelines helps to improve the refinement of the traditional operation process, so as to continuously improve the implementation of cross-border e-commerce supervision to ensure that management has clear rules to follow.

5.2 Set a buffer period to ensure that cross-border e-commerce supervision policy has a 'soft landing'

Data analysis shows that the New Deal has little impact on the import and export of cross-border e-commence. A major reason for this is that cross-border e-commerce appeared to be a 'circuit breaker' phenomenon. The State Council provided ten pilot cities with a first one-year buffer policy period, which means the New Deal did not need to be implemented temporarily. Other positive lists and tax policies remained the same, allowing cross-border e-commerce to recover quickly and develop steadily.

At the same time, because the category of the goods in the 'positive list' (although the two lists have been published) is supposed to be less than that in the New Deal, these changes directly affected the business of some enterprises. To this end, we suggest continuing to modulate the cross-border e-commerce retail import list, satisfying the demand of domestic consumers as much as possible and increasing purchasing variety, which can be supervised by regulators.

In order to further support the smooth transition and transitional development of cross-border e-commerce, we recommend keeping policy relatively stable and giving pilot cities and enterprises of cross-border e-commerce some time to adjust during the buffer period. It will boost the features of the new trade forms and the country's policy to encourage and support the healthy development of cross-border e-commerce. It is also helpful for e-commerce enterprises to adjust their supply chains, ensuring a stable transition. At the same time, as the national 'e-commerce law' and 'tariff law' is in the process of development, the proposed transition period should extend until the relevant laws and regulations are introduced.

5.3 Provide tax incentives to support foreign trade transformation

Data analysis shows that, after the New Deal, the tax burden of cross-border e-commerce enterprises is increasing, and the tax policy and tax environment have changed significantly. In the short term, because the new tax policy doesn't set a buffer period, cross-border e-commerce enterprises can't deal with it well and panic, so some enterprises tend to keep a wait-and-see attitude and their short-term business could well decrease. In the long term, after all sectors generally accept and adapt to the new tax policies, the policies can stimulate domestic demand and encourage import purchases, while favourable tax bonuses can mean that tax policies guide customers more effectively and online shopping bonded import services will enter a new development period and realise rapid growth.

Because of the openness and transparency of the internet, cross-border e-commerce can decrease business cheating and improve business behaviour. Therefore, moderate tax discounts should be provided to support the development of e-commerce. An assessment index system of the goods with favourable benefits from e-commerce, such as products with greater demand that require strict quality management (e.g. infants' products, milk powder and food) should be introduced. At the same time, policy targets can be combined to improve the global reputation of China's manufacturing products and provide favourable tax policies for cargo exportation.

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Notes

1 The study is a staged achievement of Shanghai Customs College research and innovation team on *Customs Supervision of Cross-Border E-Commerce*.

2 In fact, postal tax in China is not an independent tax, but a simple form of import tax collection.

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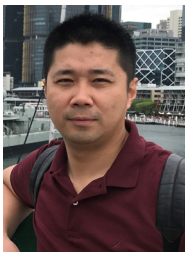

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Data analysis techniques for enhancing the performance of Customs

Danilo Desiderio

Abstract

One of the most powerful tools available to Customs to reconcile the functions of controlling the international movement of goods with the needs of trade facilitation is represented by data collection and analysis techniques. These techniques are supported by the use of statistics, algorithms and other mathematical tools, as well as by adequate IT systems for their treatment. If properly used, they can allow Customs to act in a targeted way to achieve their institutional objectives more efficiently. Customs authorities can improve the effectiveness of controls and their overall performances not only by analysing the traders' historical activity and the number of past frauds detected, but also by using additional sources of information, both internal and external to the administration. The reality, however, is that today most customs administrations use data analysis almost exclusively for conducting risk management and risk scoring activities. Instead, a holistic approach suggests that modern Customs should use such techniques also for facilitating trade, not only by minimising obstacles for operators in terms of fluidity of their operations, but by observing and analysing their behavioural patterns to introduce simplifications in customs procedures aimed to make them more user-friendly.

1. Data analysis, data warehousing and data mining

Data analysis can be defined as the process of transforming raw data into usable information, then into knowledge, in order to add value to the statistical output (Dabbicco & Di Meglio, 2011). It consists in systematically applying statistical and logical techniques to describe, summarise and compare information so that it can be used to efficiently drive priority-setting, decision-making, performance measurement, budget planning and forecasting operations.

The WCO (2018) *Draft guidance on data analytics* describes data analytics as the process of analysing datasets in order to discover or uncover patterns, associations, and anomalies from sets of structured or unstructured data, and to draw practical conclusions. The document also recommends the adoption of data analytics strategies within Customs to improve the use of available data and information, in view of expediting their decision-making process and increase their facilitation results. An example is the strategy for data analytics developed by the Canada Border Services Agency (CBSA, 2018), aimed to maximise its capacity to extract, process and evaluate all data and information needed for the efficient accomplishment of its tasks.

Data warehousing, on the other hand, is a data management technology for collecting data from multiple sources, aggregating, organising and storing them in a single repository so that they can be effectively mined. Conversely, data mining refers to the automated exploration of the data using artificial intelligence

paradigms such as machine learning or agent-based network modelling. Based on the data maturity lifecycle, data mining may start with internal available data and local providers. This could be enriched on case-by-case basis with auxiliary data available from other sources, followed by coupling external datasets.

2. Data analysis for effective border management

The World Customs Organization (WCO) dedicated the 2017 International Customs Day to data analysis for effective border management. Every year, the WCO selects a specific theme to stimulate the reflection of the global customs community on the use of new techniques and work methods that allow Customs to increase their performance, in particular through the dissemination and comparison of best practices. In 2016, the International Customs Day was opened by the WCO with the theme 'Digital Customs: progressive engagement', where customs agencies were urged to exploit the latest technologies to effectively carry out their mandate. On that occasion, WCO members were invited to use all the latest techniques and technologies, such as cloud computing or blockchain, to increase their efficiency and to improve coordination and data exchange mechanisms with other stakeholders, such as other government agencies involved in cross-border movements of goods and the trade community.

3. Internal and external data available to Customs to improve overall operations

In carrying out their routine tasks, Customs collect and generate on a day-to-day basis a huge amount of data that in most cases is underutilised by such administrations. The efficient exploitation of information in the possession of Customs is the result of a complex process, where data is interpreted, evaluated, compared and amalgamated with other information held by the administration; received from other government agencies, foreign customs administrations, regional and international organisations and private operators; or extracted by other external sources. In developing countries, additional information can be obtained by the private inspection companies conducting pre-shipment inspections (Laporte, 2011).

The need to complement internal sources with the external ones, is inversely proportional to the capacity of Customs to generate data internally. For instance, many customs administrations in developing countries, not disposing of internal databases (e.g. customs valuation databases) or having reduced internal sources of information (e.g. records on the offences and frauds detected in the past), must necessarily use additional sources to support their operations and decision-making processes (Cariolle et al., 2017). Further steps consist of integrating such data and information into the customs risk management systems and use them to develop indicators for measuring performance, both in terms of efficiency in revenue collection and trade facilitation. These actions are known (given their highly strategic and operational value) as 'customs intelligence' activities.

Data analysis, data warehousing and data mining techniques, as well as information exchanges, can greatly increase Customs' tasks of revenue collection and protection of collective interests, enhancing their ability to detect irregular declarations and illegal or suspicious movements of goods, persons and financial flows. Advanced data analytics, such as predictive analytics[1], can enable Customs to risk/rank import and export transactions and create risk scores in real time, thus facilitating compliant traders while intercepting fraudulent shipments. These techniques, when combined with information exchanges (e.g. with foreign customs administrations and other cross-border regulatory agencies) can maximise performances of Customs in the fight against frauds and other illicit activities as a result of more targeted action with minimal impediment to trade.[2]

There is, however, another aspect that must be considered. Data analytics techniques are usually used by Customs for risk management and risk scoring activities, for revenue collection, and to protect collective interests. A holistic approach suggests, however, that these techniques can also be used for facilitating trade. For example, the data generated during pilot tests of new procedures, where the behavioural patterns of private operators can be observed and analysed in order to introduce simplified procedures designed to make them more user-friendly. Another example is the time release studies (TRSs), strategic studies carried out by Customs, realised with the participation of private sector stakeholders and following a precise methodology[3], measuring the time from arrival of cargo until its physical release, for each point of entry or exit in the customs territory, so that bottlenecks in the clearance process can be easily identified and corrective actions implemented, specifically through the redesign of procedures in view of further simplifying or facilitating trade operations.

4. Major constraints in exploiting data analysis, warehousing and mining techniques

In order to efficiently exploit data analysis and data mining techniques, Customs needs to address two main constraints:

1. availability of staff with adequate knowledge and skills in data mining and who are familiar with algorithms, predictive analysis, probability models and other statistical targeting techniques

2. availability of adequate IT systems for data treatment and management.

The recruitment or identification within the customs administration of qualified staff with data mining and intelligence analysis skills can be a daunting task but is a solution that can significantly contribute to enhancing an administration's performances by improving its risk mapping and risk targeting capability. To this end, modern customs administrations should aim to create an environment that is conducive to advanced data analytics through the establishment of multidisciplinary teams made up of staff who have computer, statistics, mathematics and social science skills. This kind of approach is being pursued today by some countries, like India, where the National Academy of Customs, Indirect Taxes and Narcotics (NACEN) recently proposed a plan to recruit data mining experts and establish, within the customs administration, a Knowledge and Analysis Centre for data mining and analysis purposes.

5. Sources of data and information available to Customs

The potential sources of data and information available to Customs are today particularly numerous because of the recent advances in information and communication technologies that have drastically changed the learning behaviour of such administrations.

A list of such sources is provided in Table 1.

Table 1: Sources of information

Source	Description	Notes
Cargo and goods declarations	Cargo and goods declarations, with supporting documents, are transmitted to Customs by traders and/or their customs representatives.	Data contained in cargo and goods declarations allow Customs to learn from the traders' historical activity, so that they can conduct predictive analytics with statistical rigor aimed at forecasting their behaviour in future operations.
Results of inspections carried out by customs offices	Results of inspections can be fed into data warehouses and risk management systems and may give rise to follow-up action.	In developing countries, additional information can be extracted by the certificates issued by private inspection companies conducting pre-shipment inspections.
Data and information received from other cross-border regulatory agencies and/or regional organisations	An example of data and information received from regional organisations is given by the 'INF-AM' notifications, which are communications periodically sent by the European Anti-Fraud Office (OLAF) to the customs administrations of the European Union (EU) member states reporting on cases of fraud related to the evasion of customs duties.	Once received an INF-AM notification, the concerned customs administration is entitled to re-route the result of its risk analysis from the green (no control) or yellow (documentary control) to the red channel (physical inspection of the consignment).
Databases owned by Customs and other data held by Customs	These are, for instance, data generated during pilot tests of new procedures, and databases on customs value, on counterfeit goods or goods suspected of violating other intellectual property rights, on customs decisions regarding the classification and origin of goods, lists of registered or trusted traders (e.g. AEO), etc.	Customs valuation databases are typical risk assessment tools used by customs administration to assess potential risk regarding the truth or accuracy of the import declarations submitted by operators, by comparing the declared value to previously accepted customs values. In the EU a central AEO database is available to the customs authorities of the EU member states that allows the adjustment of the results of risk analysis for AEO-traders through a reduction of risk scoring for such operators at the moment they lodge a customs declaration.
Internal analysis or studies	An example is given by the time release studies (TRSs), which are used by Customs for re-engineering their procedures to further facilitate trade. Another example is the mirror analysis (i.e. studies where the imports reported by the importer country are compared to the exports declared by the exporter country in order to detect discrepancies in quantity, weight or declared value leading to the detection of possible irregularities).	Import/export statistics generated by Customs can also be compared with statistics produced by other organisations, such as the Commodity Trade Statistics Database (COMTRADE) of the United Nations or the WTO Data Portal, so to identify further discrepancies (undervaluation or tariff slippage).

External databases and other open source platforms	An example is the Customs Enforcement Network (CEN), a database developed by the WCO containing information on customs seizures and offences, as well as pictures required for the analysis of illicit trafficking in the various areas of Customs' competence; as well as the WIPO (World Intellectual Property Organization) Global Brand Database, a freely accessible online database with information on trademarks registered under the Madrid System for the international registration of trademarks, on appellations of origin registered under the 1958 Convention of Lisbon on the protection of appellation of origin; and on emblems protected under the 1883 Paris Convention of on the protection of intellectual property.	In the EU, the European Anti-Fraud Office (OLAF) has developed a Container Status Messages (CS) database recording the movements of containers transported on maritime vessels and an Import, Export and Transit (IET) directory containing data on goods entering, transiting and leaving the EU. These tools are aimed to strengthen the analytical capabilities of national customs authorities and OLAF in detecting fraudulent operations. Another example is the Center for Advanced Defense Studies (C4ADS), a non-profit organisation carrying out analysis on illicit trade and security risks at a global level (available online), which collaborates with the WCO in mapping illegal international trade flows in some key sectors such as: cultural heritage; drugs; environment; intellectual property rights, revenue, safety and security.

6. Conclusions

Customs administrations deal with an increasing amount of data and information, most of it made available by the recent advances in ICT. In order to efficiently handle such flows, so that they can be strategically used for informing their decisions, two preliminary activities need to be conducted:

1. diagnose and select, on the basis of qualitative criteria, those data and information that are more suitable to guide their activities in an intelligent way

2. integrate and amalgamate such information and data with those already in their possession and with those received from other government agencies, regional and international organisations and private operators.

The second activity, in turn, implies the need to harmonise and standardise data and information collected, possibly by developing appropriate IT infrastructure for their interchange/interoperability (e.g. single window). To this end, it must be remembered that the WCO developed the WCO Data Model, a set of standardised and harmonised data and electronic messages that enables the sharing of information between Customs and other cross-border regulatory agencies and can be used by them to accomplish formalities for the arrival, departure, transit and release of goods in international cross border trade.

Finally, another factor that needs to be considered is the presence of adequate legislation or regulation giving legal force and ensuring the authenticity of the documents electronically transmitted by private operators to Customs and the other cross-border regulatory agencies (e.g. electronic signature laws), as well as legislation or regulation aimed to protect the confidentiality of the data handled by such authorities.

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Notes

1 Predictive analytics is defined as analysis that uses data and algorithms to answer the question 'Given past behaviour, what is likely to happen in the future?'

2 An example of how the exchange of information between Customs can simplify trade is the development a web platform, or of interlinked national databases through which two or more customs administrations can verify the authenticity of the documents submitted by traders (e.g. certificates of preferential origin). In this context, it is also worth mentioning the initiative developed by the ICC World Chambers Federation of a website that offers a list of accredited Chambers of Commerce and Customs Authorities the possibility of verifying the authenticity of certificates of (non-preferential) origin online (https://certificates.iccwbo.org).

3 WCO, 'Guide to measure the time required for the release of goods', Version 3, 2018. With particular regard to the Central Asian Countries, WCO also developed, under the Central Asia Regional Economic Cooperation (CAREC) Program a 'Guide to Time Release Studies for Central Asian Countries'.

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Understanding tax and customs policies for retail import cross-border e-commerce in China

Xiangyang Li

Abstract

As a new industry, cross-border e-commerce continues to boom and make significant contributions to economic development. China is an important participant and benefits from the fast development of the industry, especially in retail import of cross-border e-commerce. The tax and customs policies associated with this cross-border e-commerce have been adjusted dynamically with the development of the industry, especially in recent years.

This paper examines the evolution and possible problems of tax and customs policies for retail import cross-border e-commerce in China. Section one provides an overview of development of cross-border e-commerce in China; section two gives a detailed description of the evolution of the relevant tax and customs policies; section three explains why personal postal articles and the associated tax and customs regulations are related to retail import cross-border e-commerce and how tax issues and risks arise there; and section four provides a conclusion and outlook.

1. Overview

E-commerce has been booming in China for 20 years. After two decades of growth, the e-commerce industry continues to grow, while adopting various modes (e.g. B2B, B2C, C2C). China is leading the development of the industry internationally. Significant growth in both transaction volume and number of participants in cross-border e-commerce has been witnessed in the past five years (called 'the golden era'), and it is now an indispensable part of Chinese foreign trade (Wu & Ireland, 2018). The total value of China's cross-border e-commerce in 2018 was RMB9.1 trillion and the forecast value for 2019 is as high as RMB10.8 trillion. The number of China's cross-border online shoppers is also growing quickly and could exceed 200 million by 2020. The market share of retail import cross-border e-commerce is now highly concentrated, with China's top three retail import cross-border e-commerce platforms NetEase Kaola[1], Alibaba (Tmall Global[2]) and JD Worldwide[3] representing 27.1 per cent, 24.0 per cent, and 13.2 per cent of the total market share respectively. China's top five trading partners in this sector are Japan, USA, South Korea, France and Germany (iiMedia Research, 2019).

The rapid growth of this industry is largely due to the support of both the central and local governments of China. In addition to various stimulative policies, China now has 35 pilot cities for cross-border e-commerce (Table 1 and Figure 1). In each of these cities, a **Comprehensive Pilot Area** (CPA) was officially established to support the development of the local cross-border e-commerce industry. This CPA is concentrated with various resources in order to boost the cross-border e-commerce industry in that city and hence can be viewed as a kind of business incubator. The resources may include customs

authorities, customs declaration agencies, logistics companies, express carriers, postal operators, banks and finance services firms, human resource companies, and e-commerce platforms. All these resources are dedicated to serve the needs of middle and small cross-border e-commerce in the CPA.

Table 1: Cross-border e-commerce comprehensive pilot city/area

Batch No.	City/Zone	Number	Birthday
1	Hangzhou (1)	1	7 March 2015
2	Tianjin (2), Shanghai (3), Zhengzhou (4), Chongqing (5), Guangzhou (6), Shenzhen (7), Hefe I (8), Chengdu (9), Dalian (10), Ningbo (11), Qingdao (12), Suzhou (13)	12	6 January 2016
3	Beijing (14), Hohhot (15), Shenyan (16), Changchun (17), Harbin (18), Nanjing (19), Nanchang (20), Wuhan (21), Changsha (22), Nanning (23), Haikou (24), Guiyang (25), Kunming (26), Xi'an (27), Lanzhou (28), Xiamen (29), Tangshan (30), Wuxi (31), Weihai (32), Zhuhai (33), Dongguan(34), Yiwu (35)	22	8 August 2018

Notes: The numbers in the parenthesis are used to number the cities only and do not reflect any ordering. Two more cities, Fuzhou and Pingtan, are added to the list of pilot cities for retail import cross-border e-commerce under the model of bonded import. These two pilot cities are different from CPA.

As we can see from Figure 1, the geographical distribution of all three batches of CPAs is imbalanced, with most of the cities concentrated on the nation's centre and east coast.

Figure 1: Geographical location of 35 cities with cross-border e-commerce comprehensive pilot area

Although the transaction size of import cross-border e-commerce is smaller than that of exports, import cross-border e-commerce is growing much faster than export cross-border e-commerce (Li, 2017). Hence, here we only consider import cross-border e-commerce, or more specifically, retail import cross-border e-commerce.

1.1 Business models

There are two popular business models of retail import cross-border e-commerce: bonded import and direct purchase import.[4]

Bonded import is a standard model of B2C. It refers to the model in which e-commerce traders import goods into customs special supervision zones or supervised bonded warehouses in the consumer country[5], making it possible to promptly deliver ordered goods to consumers once orders are placed online. Special customs supervision zones provide a green channel to facilitate customs clearance of these items. Goods into and out of special customs supervision zones are under the strict supervision and control of the China Customs[6], which makes the process relatively transparent. Generally speaking, the overall delivery time under this model is about 1/3 or even 1/5 of that under direct purchase import. It is one of the reasons why it is so popular in China. However, this model has its limitations. It is the importer's responsibility to decide what kind of, how many and when the products are to be imported. Hence, for example, the range of product choice for consumers could be limited since importers cannot import everything into their bonded zone warehouses.

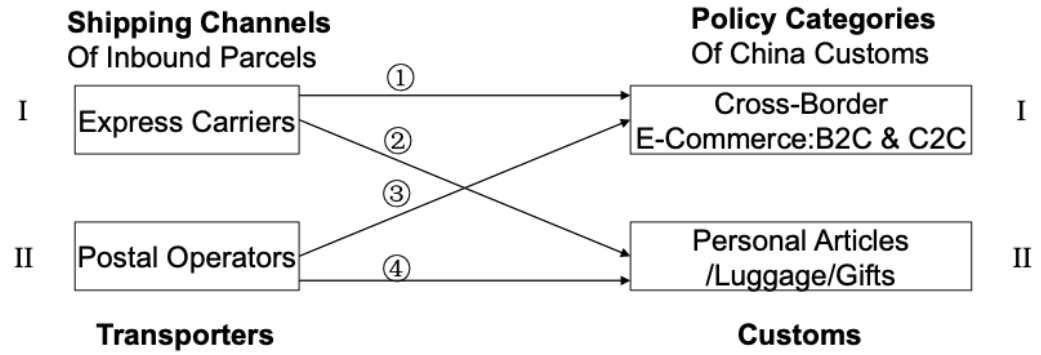
Direct purchase import is also known as overseas direct delivery. This is also a standard model of B2C. It refers to the model in which domestic consumers place orders and pay the related tax either themselves or through logistics companies on an overseas e-commerce platform. Sellers abroad then send the goods as parcels or courier items, which are then processed by customs authorities in the destination country. Under this model, delivery will usually take much more time than under the bonded import model, but the range of product choice for consumers is much larger.

In China, many cross-border e-commerce platforms like Alibaba, JD and Netease, are providing great shopping experiences for millions of Chinese consumers under the model of bonded import. At the same time, many consumers in China also order goods from overseas platforms, such as Amazon and eBay and other famous brand websites.

1.2 Shipping channels

The shipping channels of retail import cross-border e-commerce can be classified into two categories: **Category 1** is the express carriers channel and **Category 2** is the postal operators channel (Figure 2, Channel 1 and 3). Usually, the express carriers in China who are involved in cross-border e-commerce work closely with China Customs to share logistics and other related information. Examples of express carriers in China are SF express and YTO express. However, the postal operators both at home (China Post) and abroad are poorly equipped to share information with China Customs, although the situation improved in 2018, when an information system was deployed to improve the connectivity between China Post and China Customs (China Customs, 2018).

Figure 2: Possible shipping channels of cross-border e-commerce



However, personal articles, luggage and gifts, which are not deemed to be goods of cross-border e-commerce, share the same shipping channels (Channel 2 and 4) as illustrated in Figure 2. China Customs has different policies (tax and clearance procedures) for cross-border e-commerce and personal postal articles, which could pose a potential tax risk and needs further consideration (this will be covered later).

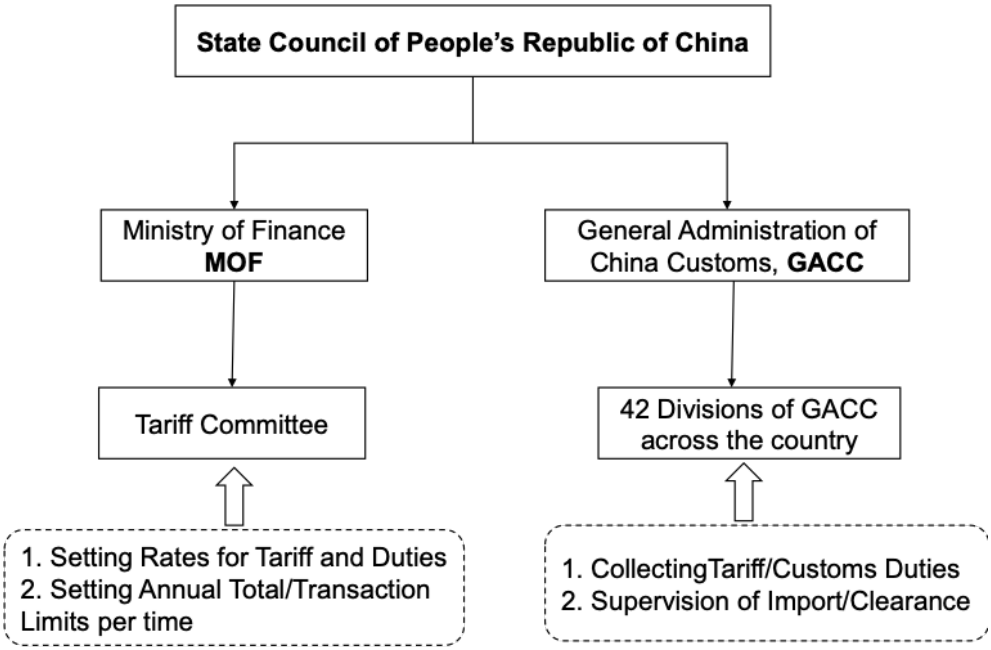
2. How retail import cross-border e-commerce is regulated

2.1 Regulatory bodies

There are 11 departments in State Council that are potentially involved in the administration of cross-border e-commerce in China, although only two of these departments are directly involved in regulation and supervision of cross-border e-commerce, as shown in Figure 3. These are the Customs Tariff Commission (CTC) in the Ministry of Finance (MOF) and China Customs – General Administration of China Customs (GACC). The CTC is responsible for setting the customs tariff and duty for imported goods, as well as the annual total limit and each transaction limit for individuals involved in cross-border e-commerce. GACC is responsible for enforcing the rules and policies set by CTC and collecting tariff and duty. To ensure the smooth supervision of imports and the legal and effective clearance of goods, GACC will set its own rules to be obeyed by all participating parties, including e-platforms, e-vendors, e-payment operators, e-platform providers (either self-run or a third-party), and logistics operators involved in cross-border e-commerce.

Circular No. 26 on Issues Concerning the Supervision of Retail Imports and Exports in Cross-Border E-commerce, issued by GACC in April 8, 2016, among other things, was the principal Customs regulation on cross-border e-commerce, although changes have been made since then. The circular applies to all individuals and companies that engage in retail imports and exports in cross-border e-commerce. GACC has created many clearance patterns to better fit different business models in cross-border e-commerce, as stated in Section 1.[7] GACC also deployed an information system called *Import Cross-Border E-Commerce Unified Edition* to further facilitate the supervision of clearance of goods in retail import cross-border e-commerce.

Figure 3. Regulatory bodies of import cross-border e-commerce



2.2 Evolution of tax and customs policies

In the last few years, the tax and customs policies of cross-border e-commerce have experienced dramatic changes. The tax and customs policy period can be roughly divided into two periods: before and after 8 April 2016. The policy before 8 April 2016 can be called the **old policy** since it is abolished now. The policy effective on or after 8 April 2016 can be called the **new policy,** or more popular, the **'April 8' new policy**. Although a few changes have been made to the **'April 8' new policy** since 8 April 2016, its essentials remain intact. This 'April 8' new policy is completely different from the old policy.

Three features of 'April 8' new policy[8]

Under the old policy, imported goods in cross-border e-commerce were treated as personal articles and hence subjected to personal postal article tax regulations (a kind of integrated tax system for different categories of personal articles)[9] and purchases were eligible for an exemption of payable duties up to RMB50 (also called 'de minimis threshold', DMT hereafter). The customs clearance was simple and there were no complicated procedures and documents needed for quarantine clearance purposes.

The 'April 8' new policy was completely different. There are three notable features that deserve detailed discussion.

1. Integrated tax was introduced and DMT was cancelled. Under the 'April 8' new policy, imports in cross-border e-commerce were no longer treated as personal articles.[10] Instead, they were treated as goods imported under the general trade system and hence were subjected to tariff, VAT and consumption tax, but not in full value. This integrated tax was called the preferential integrated tax. The preferential integrated tax (also called comprehensive rate) of cross-border e-commerce was only 70 per cent of that under general trade system and the tariff rate of cross-border e-commerce is temporarily set to zero.

To be specific, let R_{all}, R_{vat}, R_{tar}, R_{con}, denote the preferential integrated tax rate for the import goods in cross-border e-commerce, VAT rate, customs tariff and consumption rate for goods in the general trade system respectively, then we have: $R_{all} = 70\% * (R_{vat} + R_{tar} + R_{con})$

Under the 'April 8' new policy, customs tariff is set to zero, $R_{tar} = 0$. For most of items, consumption rate is zero too. So we assume that $R_{con} = 0$. The VAT rate in China has been subjected to a few changes since 2018. Before 1 May 1 2018, the VAT rate for most imported items was 17 per cent, hence $R_{all} = 11.9\%$. This means that most items imported in cross-border e-commerce are subject to an integrated tax at a rate of 11.9 per cent, which is lower than the adjusted personal postal article tax rates and also the integrated tax rate for goods imported under general trade. The VAT rate has been adjusted twice since 1 May 2018, first to 16 per cent and now it is 13 per cent. Hence, $R_{all} = 9.1\%$ now for most items, which is even lower than before.

DMT was cancelled under the 'April 8' new policy. This means that the integrated tax must be levied no matter how small it is. This cancellation was introduced due to the risk monitored by the government. Cross-border e-commerce importers usually divided large value orders into small value ones so that the duty payable fell below DMT and hence tax evasion occurred. The cancellation of DMT put an end to this tax risk problem.

At the same time, annual transaction limits and individual transaction limits for individuals were introduced. The annual transaction limit is RMB20,000 and each transaction limit is RMB2,000 (see Table 2). Single inseparable goods that exceed the maximum transaction value (i.e. RMB2,000), or accumulated transactions that exceed the annual total, are treated as traditional trade goods and the full value of customs tariff, VAT and consumption tax applies.

2. Customs Clearance Certificate and related documents were required for clearance. Before the 'April 8' new policy, commodities imported through cross-border e-commerce platforms were deemed to be personal postal articles and hence subjected to much simpler inspection and quarantine procedures in customs clearance than under the traditional general trade system. Under the 'April 8' new policy, when such goods were no longer treated as personal postal articles, the customs clearance procedures became complicated, much like the procedures for traditional general trade. As part of the customs clearance process, quarantine procedures for some of the products imported through cross-border e-commerce, like baby formula, cosmetics and medical devices, became much more complicated and sometimes impossible to satisfy. Importers needed extra certificates, like a certificate of origin, import licence, permits and registrations in related supervision departments in order to meet the requirements of import quarantine procedures. The application and acquisition process for licences and permits were very costly, both in time and money, and sometimes even impossible for small importers. In this sense, this new policy posed a great challenge to those who import products like baby formula, cosmetics and medical devices, especially to small importing businesses.

3. The 'Positive List' was introduced. Generally speaking, under the old policy, except for restrictive or prohibited items, like radioactive products, dangerous chemicals and waste, and used articles, almost all goods could be imported through cross-border e-commerce without any restrictions. However, the 'April 8' new policy brought this to the end. After the release of the *List of Cross-Border E-Commerce Retail Imports* (the so-called 'positive list', first batch) by 11 departments, including the Ministry of Finance, the National Development and Reform Commission (NDRC) and GACC, on 7 April 2016 (effective on April 8, 2016), only goods bearing the harmonised system (HS) codes shown on the list can be imported for cross-border e-commerce and sold through cross-border e-commerce platforms. Any goods that are not on list must be imported under the traditional general trade system. The list covers 1,142 tariff lines (commodities) under the 8-digit HS codes. These are mainly daily consumer goods that have a considerable demand in China. Included on the list were certain food products (fresh or dried fruit, dairy products, seafood, seasoning and dressing product for foods, rice, honey product etc.), beverages, garments, footwear and headgear, watches, home appliances and kitchenware, as well as certain cosmetics, paper nappies, baby formula, children's toys and thermal mugs.

Table 2: Evolution of policies

	Old policy: before 8 April 2016	New policy: effective 8 April 2016, 'April 8' new policy	Amended 'April 8' new policy: effective 1 January 2019
Payable duties RMB 50 or less (De minimis Threshold, DMT)	Exempted	No exemption	No exemption
Maximum value allowed per transaction	RMB 1,000	RMB 2,000	RMB 5,000
Annual total/limit per person	Not applicable	RMB20,000	RMB26,000
Applicable tax rate	10%, 20%, 30% and 50%, depending on the category of goods	Comprehensive rate = 70%* (Tariff rate temporarily set at 0% + VAT 13% + consumption tax rate depending on the category of goods)	
A single inseparable goods that exceeds the maximum value in a transaction	Will be treated as traditional trade and therefore subject to 1. Customs duty 2. VAT 3. Consumption tax		Comprehensive Rate = 100%* (Tariff rate of the goods as general trade +VAT 17% + consumption tax rate depending on the category of goods)
Positive List	–	1142 tariff lines – first batch 151 tariff lines – second batch	1321 tariff lines

Notes: Customs tariff, consumption tax and VAT are all cumulative taxes. The tax base for customs tariff is the goods price (including shipment cost and insurance, i.e. CIF). The tax base for consumption tax is the goods price plus customs tariff. The tax base for VAT is the sum of goods price, customs tariff and consumption tax.

Market response to 'April 8' new policy

The cross-border e-commerce industry was completely shocked after the release of the 'April 8' new policy, especially as a result of the second and third features (or requirements).

The first requirement, the wholly new integrated tax policy, was not the most lethal one to the industry, although there were some negative impacts due to the annual limit for each consumer, the per-transaction limit for each consumer and the cancellation of DMT. These negative impacts were not that big and were still acceptable to the industry. Furthermore, the actual tax burden of the new integrated tax policy was not necessarily higher than that of the previous tax policy and, depending on the type of goods, was sometimes lower.

The second and the third requirements, however, were lethal to the industry. For the second requirement, numerous cross-border e-commerce platforms or operators found that they were unable to clear some commodities through Customs due to the requirement of quarantine procedures. This is because most importers/operators in cross-border e-commerce were unable to obtain documents, like certificates of

origin, import licences, permits and registration filings in related supervision departments. As such commodities were in high demand by Chinese consumers, many operators in the industry were unable to conduct their business anymore.

The third requirement, the 'positive list' was another lethal blow to the industry. Though the positive list (first batch) has tried to cover a lot of commodities that can be imported and sold through cross-border e-commerce, there were still some commodities not covered. Immediately, some importers found themselves being unable to import the products they used to sell. This was the reason why the second batch of the positive list was released shortly after the first batch.

The whole industry was trembling after the release of the new policy. Something had to be done immediately to tackle the problem.

What has the government done since 8 April 2016?

Due to the strong and unexpected impact, the government acted quickly and effectively to minimise the impact on the industry and finally achieved a smooth transition.

First, the government announced a second batch of the 'positive list' to try to include more commodities and reduce the negative impact. On 15 April 2016 (effective 16 April 2016), 13 departments (including MOF, GACC and the NDRC) jointly released the *List of Cross-Border E-Commerce Retail Imports* (the so-called 'positive list', second batch). The list covers an additional 151 tariff lines (commodities) under the 8-digit HS codes and included more food (fresh or dried fruit, fish oil product, rice, vegetable oil etc.) and other products (some medical products).

Second, the government announced a transitional period to address the problems caused by the second requirement. A one-year transitional period (May 2016 to May 2017) was offered for supervision requirements, especially for the quarantine procedures in customs clearance stipulated in the *List of Cross-Border E-Commerce Retail Imports* (both in the first and second batch). Until 11 May 2017, 'bonded imports' entering the bonded zones in the 10 cross-border e-commerce pilot cities were exempted from checks of their customs clearance certificates. Import permits, registration or filing was not required for first-time imported cosmetics, baby formula, medical equipment and special food products (including health food product and food for special medical purpose). Import permits, registration or filing requirements were also exempted for 'direct purchase imports'.

The transitional period was extended twice until a new policy came out at the end of 2018, following the State Council's decision to adopt an expanded cross-border e-commerce regime. The latest policy[11] (effective 1 January 2019) is an amendment of the 'April 8' new policy. There are also some notable features that deserve mentioning (see Table 1).

First, the goods in cross-border e-commerce are no longer deemed as goods under the general trade system. They are now officially deemed as 'personal articles' again, as in the old policy.[12] This means that there is no need for customs clearance certificates and related documents at customs clearance. This is a special category of 'personal articles' since the goods are still subject to the preferential integrated tax under the 'April 8' new policy and not subjected to personal postal articles tax regulations as in old policy.

Second, both the annual limit and per-transaction limit for each individual have been increased. The annual limit has been raised 30 per cent up to RMB26,000 per year, and the transaction limit has been raised from RMB2,000 to RMB5,000.

Third, the 'positive list' has now been updated to include 1,321 tariff lines to meet the needs of consumers.[13]

Fourth, comprehensive provisions have been laid out for customs supervision of goods in the positive list. GACC released two more specific announcements for supervision purposes a few weeks after the release of the amended 'April 8' new policy.[14]

Finally, the impacts of the 'April 8' new policy on the market are greatly relieved by the amended 'April 8' new policy. The transition of the 'April 8' new policy has gone smoothly, without causing too much harm to the industry.

3. Personal articles regulations

Since personal articles and retail import goods in cross-border e-commerce share the same shipping channels, it is hard to determine whether an inbound parcel is a personal article or goods in cross-border e-commerce. This is the case especially in poorly regulated channels like the postal operator channel, although the situation is improving. Since personal articles still enjoy the preferential tax policy (DMT policy) while goods in cross-border e-commerce do not, evasion of tax by importers could still potentially exist. This is the essential reason why regulations for personal articles are reviewed here.

3.1 Evolution of personal articles tax regulation

The term 'personal article' or 'personal postal article', also known as luggage and postal articles, can be referred to as inward/outward passenger baggage, mail packages, and gifts exchanged between relatives and friends, deemed as for personal use only.

All such inbound personal articles must be limited to a 'reasonable quantity'. China Customs does not give an exact quantity limit for different kinds of personal articles, but an overall value limit and also a DMT of RMB50 is set.[15]

First, China Customs levies an import duty on personal articles mailed from outside the mainland, with a DMT of RMB50. This is a so-called 'personal postal article tax', which is a type of integrated tax rate. Different categories of personal articles have different integrated tax rates as indicated in Table 3).[16]

Second, personal articles mailed from or to Hong Kong, Macau or Taiwan should be worth no more than RMB800, and personal articles mailed from or to other countries and regions, should be valued at no more than RMB1,000. Within this limit, import duty will be levied according the Schedule of Import Duty Rates in Table 3.

Third, in the case of personal articles with an overall value exceeding the above-mentioned limit, the mail may be returned or cleared by Customs in line with the traditional general trade regulations. If, however, any mailing consists of just one item and still exceeds the specified value limit, the import of the package must firstly be approved by China Customs first. If it is indeed for personal use only, the tax rates in Table 3 are applicable.

Due to the quick growing demand of consumers in China, the personal articles regulation (tax rates and categorisation) also evolved quickly, especially in recent years. The policy period can be roughly divided into four periods (see Table 3).

The trend for the policy evolution is clear. The categorisation for personal articles becomes simple for easier clearance and the tax rates are generally decreasing to encourage more import and consumption.

Table 3: Schedule of import duty rates for personal articles

Policy 1: before 8 April 2016[17]	**Tariff Category No**	**1**	**2**	**3**	**4**
	Applicable categories of goods	• Books & magazines • Educational films & slides • Audio & visual recording tapes • Gold & silver products • Computers • Video recorders • Digital cameras • Food & beverages • Other goods not included in category 2, 3 & 4.	• Textiles • TVs, cameras & other electrical appliances • Bicycles • Watches, clocks & their parts & accessories	• Golf clubs & equipment • High-end watches	• Tobacco • Wine • Cosmetics
	Tax Rate	10%	20%	30%	50%
Policy 2: Effective after 8 April 2016[18]	**Tariff Category No**	**1**	**2**	**3** Note 1	
	Applicable categories of goods	• Food & beverages • Books & magazines • Educational audio-visual products • Gold & silver products, • Computers, video recorders, digital cameras • Furniture • Toys, games, festive & other recreational articles	• Sports goods (excluding golf clubs & equipment) • Fishing tackle, • Textiles & textile products • TVs, cameras & other electrical appliances • Bicycles • Other goods not included in category 1 and 3.	• Tobacco • Wine • Cosmetics • Golf clubs & equipment • High-end watches • Precious jewellery & jade	
	Tax Rate	15%	30%	60%	
Policy 3: Effective after 1 November 2018[19]	**Applicable categories of goods**	The same as Policy 2 plus medicines Note 2	The same as the Policy 2	The same as Policy 2	
	Tax rate	15%	25%	50%	
Policy 4: Effective after 9 April 2019[20]	**Applicable categories of goods**	The same as Policy 2 plus medicines Note 3	The same as Policy 3	The same as Policy 3	
	Tax rate	13%	20%	50%	

Note 1: Items listed under category No. 3 in Policy 2, 3 and 4 falls within the scope where consumption tax levied.

Note 2: Imported cancer drugs, which are subject to VAT at a reduced rate of 3% according to state regulations are levied at the same level as standard rate for dutiable goods.

Note 3: Imported drugs, including cancer drugs, which are subject to VAT at a reduced rate of 3% according to state regulations are levied at the same level as standard rate for dutiable goods.

3.2 Personal articles regulations

As shown in Figure 2, inbound personal articles and cross-border e-commerce share the same shipping channels. Since the personal articles (non-traded goods) and cross-border e-commerce goods (traded goods) are subjected to different tax policy systems, tax risks may arise, particularly tax evasion by importers who illegally claim cross-border e-commerce goods to be personal articles. The reason for this is that DMT was cancelled for cross-border e-commerce goods but still applies to the personal articles. The importers or the sellers have the motivation to do so to by dividing large value orders into several small value orders so that the duty payable on each small order is below DMT. By disguising the small value goods as personal articles, payable duties will be incorrectly waived. Another reason is that the two kinds of goods share the same shipping channels, which makes the deception easy to carry out.

Under the direct purchase import model, numerous goods are sent through postal channels as personal articles and DMT policy may apply naturally in these cases, and hence the tax evasion problem is greater under the direct purchase import model.

This potential tax evasion risk is yet to be fixed. China Customs should endeavour to establish connections with overseas sellers to exchange order and logistics information.[21] This will be helpful in dealing with tax evasion problems and may assist in addressing the problem.

4. Way forward

The 'April 8' new policy in 2016 (in Table 2) is a milestone policy for retail import cross-border e-commerce. After three years of transition and long discussions and debates among the industry and the government, the goods of retail import of cross-border e-commerce retail imports are finally being treated as special 'personal articles' (amended 'April 8' new policy in Table 2). This means that the amended 'April 8' new policy abolishes the second requirement and retains the first and third requirement of the 'April 8' new policy. This amended new policy, which came into effect on 1 January 2019, has minimised the negative impact on the market caused by the 'April 8' new policy. It was widely accepted by the industry and so it is likely that it will be at least a few years before any further changes are made.

However, as long as the DMT policy is applicable to imported personal articles and not to goods in cross-border e-commerce, tax evasion problems may still be unavoidable, although the situation is improving with the increasing connectivity between participants such as logistics firms and China Customs.

As consumer demands continue to grow in China, so will retail import cross-border e-commerce.

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Notes

1 NetEase Kaola: www.kaola.com

2 Tmall Global: https://import.tmall.com

3 JD Worldwide: https://www.jd.hk

4 Here we only consider the B2C models. The C2C model is not of interest since it is not under the control of customs authorities and the data and statistics about this model are not available. 'Retail' here means '2C', i.e. the goods are sold to final consumers. China Customs code for bonded import model is 1210 and for direct purchase import model is 9610.

5 This import from overseas to domestic warehouses is usually carried out under the traditional general trade system, which is the first part of B2C. For the second part of B2C, i.e. the '2C' part, is usually carried out through cross-border e-commerce system.

6 Now the Quality Supervision, Inspection and Quarantine Bureaus of China is part of the China Customs due to the institutional reform of State Council in 2018.

7 Two popular business models for import cross-border e-commerce will be introduced later.

8 These three notable features can also be viewed as requirements by the government that must be fulfilled or obeyed by the industry.

9 Personal postal article tax regulations will be introduced in Section 3.

10 Personal articles are subjected to personal postal article tax regulations that are different from the tax regulation on the goods imported in traditional general trade system. Generally speaking, the personal article or personal postal articles is deemed as **non-traded goods,** contrasting to **traded goods** in traditional general trade system. More details will be covered later.

11 Circular on Issues Concerning Improvement of Supervision of Retail Import of Cross-Border E-Commerce (No. 486 [2018]), http://www.gov.cn/xinwen/2018-12/01/content_5345041.htm (in Chinese). This circular was jointly released by six departments of State Council.

12 The characteristic of the goods under cross-border e-commerce now is somewhere between goods under general trade system and personal articles.

13 The positive list will continue to be updated according the consumer needs and other factors.

14 First, GAC Announcement No. 219 (2018) (Announcement on Matters Pertaining to Customs Registration of Cross-Border E-Commerce Enterprises), http://www.customs.gov.cn/customs/302249/302266/302269/2163193/index.html (in Chinese); Second, GAC Announcement No.194 (2018) (Announcement on Matters Pertaining to Regulation of Cross-Border E-Commerce Retail Imports and Exports), http://www.customs.gov.cn/customs/302249/302266/302269/2140731/index.html(in Chinese).

15 Circular on Issues Concerning the Adjustment of Supervision Measures of Inbound and Outbound Personal Postal Articles (No.43 [2010]), http://www.gov.cn/fwxx/sh/2010-08/10/content_1675428.htm (in Chinese). For personal articles carried back to China by individuals will subject to a different tax regulation. Here we only consider personal articles mailed back to China.

16 There are twenty kinds of goods that will not be exempted from payable duty no matter how small it is.

17 Circular of Issues Concerning the Adjustment of Import Tax on Personal Articles (No. 3 [2011]), http://gss.mof.gov.cn/zhengwuxinxi/zhengcefabu/201101/t20110126_429432.html (in Chinese).

18 Circular of Issues Concerning the Adjustment of Import Tax on Personal Articles (No. 2 [2016]), http://gss.mof.gov.cn/zhengwuxinxi/zhengcefabu/201603/t20160324_1922971.html (in Chinese).

19 Circular of the State Council Customs Tariff Commission on Issues Concerning the Adjustment of Import Tax on Personal Articles (No. 49 [2018]), http://gss.mof.gov.cn/zhengwuxinxi/zhengcefabu/201809/t20180930_3033433.html (in Chinese).

20 Circular of the State Council Customs Tariff Commission on Issues Concerning the Adjustment of Import Tax on Personal Articles (No. 17 [2019]), http://gss.mof.gov.cn/zhengwuxinxi/zhengcefabu/201904/t20190408_3216190.html (in Chinese).

21 Though it is required that overseas sellers should be registered in GACC before they can carry out retail import cross-border e-commerce in China, there are still some sellers that may not be able or unwilling to do so.

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Section 2

Academic Contributions on WCO Data Analytics

Introduction

The following papers on data analytics were prepared as a result of recent World Customs Organization (WCO) workshops that examined ways in which customs administrations could take greater advantage of the huge amount of data that is available to them. Recognising that such data is currently underused, the workshops focused on data analysis methods that could be used to help administrations gain a better understanding of themselves and the work they do, and to help identify ways to develop more efficient and effective customs administrations at both the operational and strategic levels. The workshops concluded that enhancing Customs' ability to perform increasingly sophisticated analytics using the available data will become even more crucial in all future policy-making processes, and participants were encouraged to make greater use of data analytics as a key tool for more robust analyses.

Establishing risk and targeting profiles using data mining: Decision trees

Bassem Chermiti

Abstract

The application of technology and the computerisation of management processes in customs administrations have undoubtedly accelerated the processes related to data storage.

In this context, customs administrations possess vast amounts of data on trade and financial flows. Data mining tools can be effective in analysing huge reams of data. Data mining consists of understanding, preparing, modelling and analysing data using different techniques, such as machine learning. Many of these techniques have advanced predictive analytical capacities that can ultimately lead to improved analytical capabilities in risk management.

The Chi-square Automatic Interaction Detector (CHAID) decision tree method was selected for the purposes of this paper to determine the customs risk factors associated with import declarations recorded in the customs clearance system. The CHAID method is also used to create risk profiles and predict non-compliant customs declarations based on established rules.

1. Introduction

In contemporary society, data processing has the potential to improve the quality of management decisions. Moreover, analyses of economic activity over recent decades has shown the impact of technology (such as the computerisation of almost all trading processes), which has led to increased storage of a considerable amount of data.

Customs administrations have a large amount of data on trade and financial flows. However, the quantity of data available is less important than what the administrations do with it. Only robust analyses can make this data useful and usable in the decision-making processes.

Cognisant of this importance, the World Customs Organization (WCO) dedicated the year 2017 to data analysis and used the slogan 'Data analysis for Effective Border Management'. The aim was to encourage member countries to further promote their efforts and activities in a vital and indispensable sector of the customs modernisation process: data collection and analysis.

Data mining enables the examination and exploitation of stored data. It has developed as a multidisciplinary approach capable of analysing a large amount of data and identifying significant models.

Data mining has developed very rapidly with the support of technologies and sciences, such as statistics, artificial intelligence and machine learning. Indeed, there is a wide range of data mining methods that can be used to solve multiple issues, some of which have been used for risk management purposes in the customs domain (Geourjon, Laporte, Coundoul, & Gadiaga, 2012).

In recent years, machine learning and artificial intelligence have garnered significant interest and popularity, particularly in the financial field, with the expectation that their introduction will result in an improvement in analytical capabilities, including risk management.

In the customs context, risk management is one of the key measures contained in the World Trade Organization's (WTO) Trade Facilitation Agreement (TFA), and in the WCO's Revised Kyoto Convention (RKC). In operational terms, customs risk management is an effective way to handle trade flows with a guarantee of trade fluidity as only the most risky goods are targeted. The objective is to obtain controls adapted to the risk profiles that are determined.

In order to isolate risky shipments, several methods have been implemented by customs that are largely based on the exchange of information, in-depth analysis of fraud trends and the review of available information on traffic flows and trade patterns.

In this paper, we will use machine learning as a tool for identifying and analysing customs risks. We will also use the decision tree method, which is particularly suitable for data mining and enables the development of predictive models.

The CHAID (Chi-Square Interaction Detector) method is one of the most common decision tree algorithms and features among the most popular data mining techniques. Among the many researchers who have used this method are Ôcal, Ercan and Kadioglu (2015), who used the CHAID method to predict the financial crisis, and Koyuncugil and Ozgulbas (2017), who used it for financial profiling and operational risk detection.

This method is used to uncover new information in large databases, to detect unspecified interactions between variables, and to create predictive models.

Our study was conducted using data obtained from a partner customs administration in the framework of a seminar organised by the WCO to highlight the utility of data analysis in the customs domain.

This study is composed of two sections. The first section focuses on data mining, particularly machine learning, to leverage stored information and the decision tree method as explored through the CHAID algorithm, which we will apply in the context of customs risk management.

The second section focuses on the empirical study of data sourced from the partner customs administration in an effort to develop a predictive model for detecting non-compliant import declarations and risk profiles based on detected risk factors.

2. Data mining, machine learning and decision trees

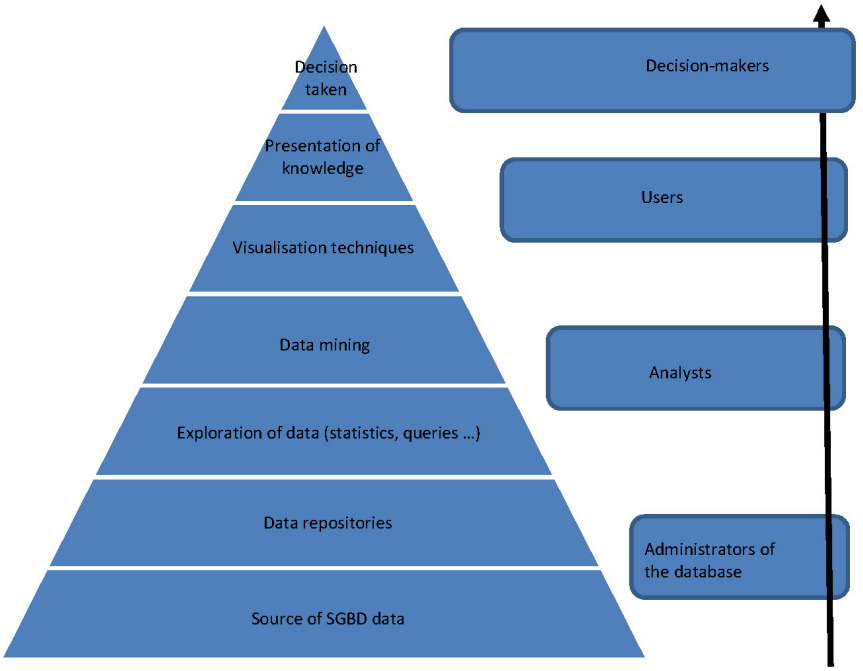
2.1 Data mining

'Data mining, *the extraction of hidden predictive information from large databases*, is a powerful new technology with great potential to help companies focus on the most important information in their data warehouses. Data mining tools predict future trends and behaviors, allowing businesses to make proactive, knowledge driven decisions' (Thearling, 2003).

Data mining is a combination of computer and statistical techniques designed to perform an exploratory data analysis. These techniques have been applied in several areas, such as fraud detection, tourism, industry, marketing, finance and customs. From the flow of raw information to underpinning relevant decision-making, data mining is an appropriate tool that enables data analysis.

In this context, the pyramid below outlines the responsibilities of the actors in the decision-making process. The database administrator designs, manages and administers database management systems and data warehouses, while analysts extract information by running queries and using various techniques, including data mining, to assign meaning to the data stored in the databases. The results are intercepted by users, who in turn share the information with decision makers to allow for optimal decision-making.

Figure 1: Information flow and participants



Source: Rakotomalala Course, 'Introduction to Data Mining', University Lumière Lyon 2.

Data mining is therefore at the centre of the process of uncovering information contained in databases. According to Fayyad, Piatetsky-Shapiro and Smyth (1996), this process begins with the selection of data, which is a two-step process: first, it is crucial to develop and understand the application domain and the existing information; second, a set of target data is created from which the discovery will be made. The result is the acquisition of target data.

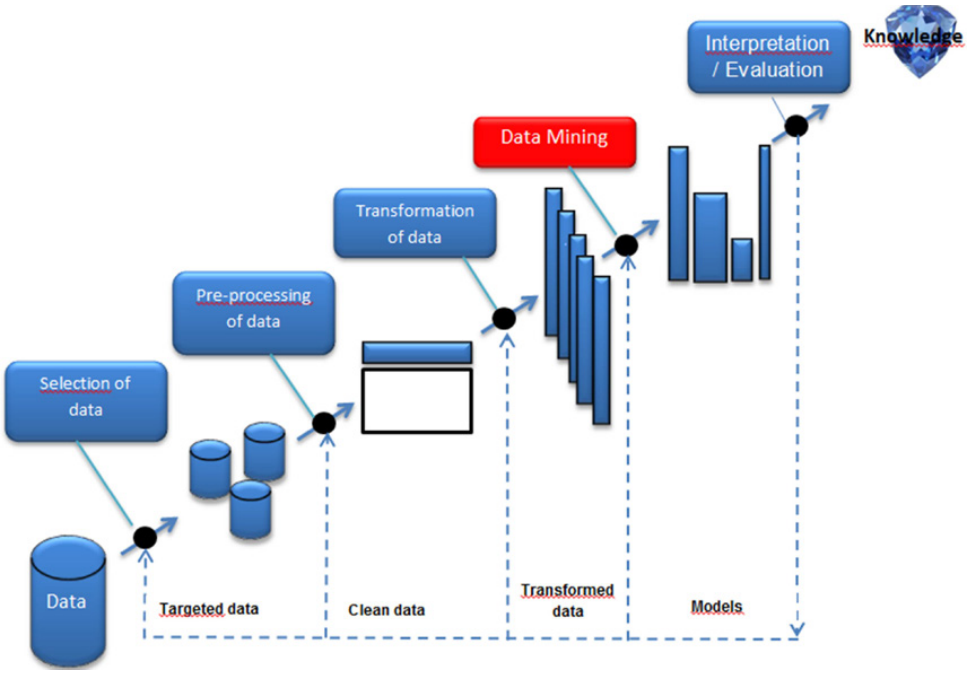
Data pre-processing is the second step in this process and involves processing noisy and missing data. The goal is therefore to ensure that the process model of information discovery in databases produces accurate results. The legacy of this step is the acquisition of cleaned or pre-processed data.

The transformation of data represents the final step. This is the final stage of data processing before data analysis techniques are applied. It consists of finding useful attributes by applying dimension reduction and transformation methods and finding an invariant representation of the data; the result is transformed data. This phase is followed by the most important step, data mining, which consists of choosing the appropriate algorithms or methods, and matching the specific objectives with these methods (regression, classification, trees, grouping, etc.) in order to find and apply appropriate data mining prototypes. This final step results in models.

This process ends with an interpretation and evaluation phase, which outlines the information uncovered. If the result obtained is not considered significant, a new iteration is necessary. The interpretation and evaluation phase can also feature visualisations of the extracted models. The information then needs to

be consolidated by integrating it into the performance system, or simply documenting it and reporting it to the appropriate units. This step can include checking and resolving any potential conflicts with information previously created. The outcome is knowledge.

Figure 2: Process of knowledge discovery Fayyad, Piatetsky-Shapiro and Smyth (1996)



Note also that data mining differs from conventional statistical techniques in its artificial intelligence capacity. It uses several techniques and technologies, such as statistics, machine learning techniques and SQL query language.

Figure 3: Data mining techniques

3. Machine learning and decision trees

3.1 Machine learning

Machine learning is a method used in data mining. It consists of algorithms that analyse a set of data in order to deduce rules constituting new knowledge and to analyse new situations.

This method is capable of analysing vast volumes of data, while providing in-depth predictive analysis. Perhaps as a result, machine learning and artificial intelligence have received unparalleled attention in recent years.

However, administrations that possess a large amount of data clearly need powerful analytical tools to manage that data. Machine learning is widely regarded as a technique that can provide this analytical power to model complex, non-linear relationships.

Machine learning includes a range of analytical tools that can be classified as 'supervised' and 'unsupervised' learning tools. Supervised machine learning involves the creation of a statistical model to predict or estimate a result based on one or more inputs (in our case this article predicts the non-compliance of a customs declaration registered in the IT system of the partner administration in accordance with several variables or risk factors).

In unsupervised learning, a set of data is analysed with no dependent variables to estimate or predict. Instead, data is analysed to show patterns and structures in a dataset.

Machine learning can also be a particularly powerful tool when it comes to forecasting. Certainly, because of its ability to process a large dataset and its computational power, machine learning is closely associated with the 'Big data revolution'.

According to Thearling (2003), the most used technique in data mining is decision trees, which are tree-like structures representing sets of decisions that generate rules for classifying a dataset. Specific decision tree methods include classification, regression (CART) and automatic detection of interactions with chi-square (CHAID). There are also artificial neural networks that represent another data mining technique that enables complex problem solving by adjusting weighting coefficients in a learning phase. There are also genetic algorithms—an optimisation technique that uses processes such as genetic combination, mutation and natural selection in a model that is centred on the concepts of evolution. An additional method, nearest neighbour, groups each record into a set of data based on a combination of the most similar classes of k records contained in a group of historical data. This technique is also called k-nearest neighbour (k_NN).

In the context of this study, we use the decision tree technique, specifically the CHAID method.

3.2 Decision trees

The decision tree is a non-parametric supervised learning method used for classification purposes and for the development of predictive algorithms. The objective in using decision trees, in this article, is to create a model that predicts the value of a target variable by learning simple decision rules derived from the characteristics of the data.

Decision trees are constructed by seeking, through the successive fragmentation of the training set, partitions in the space of the optimal predictors capable of predicting the modality of the response variable. Each rupture is done in accordance with the values of a predictor. During the first step, all the predictors are tested in order to identify which are best. Then the process is repeated at each new node until a stop criterion is satisfied. The determination of the best rupture at each node is made in accordance with a local criterion. The choice of criterion is the main difference between the various existing methods of tree induction. Among the most frequently used criteria are:

- Shannon's entropy, applicable to all types of explanatory variables. This measure is used by Quillan in C4.5 and C5.0 to measure uncertainty:

$$Entropy\ (node_t) = \sum_{i=1}^{k} - f_i \log_2 f_i$$

Where $f_i, (i = 1, \ldots, p)$ are the relative frequencies in the node t of k classes to predict.

- The CART algorithm produces binary decision trees and applies the Gini index, called quadratic entropy, to select the explanatory variables of any type.

$$Gini\ (node_t) = \sum_{i=1}^{k} f_i (1 - f_i) = 1 - \sum_{i=1}^{k} f_i^{\,2}$$

- The CHAID method, outlined below.

3.3 The CHAID method

CHAID is one of the oldest classification tree methods and was proposed by Kass (1980). Unlike other tree algorithms, the CHAID method can build non-binary decision trees.

CHAID modelling is an exploratory data analysis method used to study the relationships between a dependent measure and a large set of possible predictor variables that may interact with one another. The dependent measure may be qualitative (nominal or ordinal) or quantitative.

For qualitative variables, a series of chi-square analyses is performed between dependent and predictive variables.

For quantitative variables, variance analysis methods are used when intervals (disaggregation) are optimally determined for independent variables to maximise the ability to explain a dependent measure in terms of components of variance (Thearling, 2003).

The Chi-square test value is calculated using the formula:

$$\chi^2 = \sum_{i=1}^{k} \sum_{j=1}^{m} \frac{(n_{ij} - previj)}{previj}$$

$$\text{or } previj = \frac{n_{i.} \times n_{.j}}{n}$$

- n_{ij} is the number in the box marked by row i and column j
- $n_{i.}$ is the marginal size of line i
- $n_{.j}$ is that of column j
- n is the total number (the size of the population)
- previj: the expected strength for the cross-analysis field in row i and column j.

The theoretical test is then applied with a level of significance chosen by the user to check whether there is independence between the crossing of the two variables.

The decision tree consists of:

- Root node: The root node contains the dependent or target variable. For example, in our case, we want to predict the non-conformity of a declaration according to details such as the origin of the goods, the quantity and the declared value, the risk of non-conformity is the target variable and the factors remaining are the predictor variables.
- Parent nodes: The algorithm divides the target variable into two or more categories. These categories are also known as initial nodes.

- Child nodes: The categories of independent variables that are below the parent categories in the CHAID tree.
- Terminal nodes: The last categories of the CHAID analysis tree. In the CHAID analysis tree, the category that has a major influence on the dependent variable comes first, and the least important category comes last.

The process of building a CHAID decision tree is divided into three parts:

1. Select the relevant independent variables from the input variables. The first variable selected to divide the data is the variable with the lowest p-value and therefore the most strongly associated with the dependent variable. By applying the hypothesis test, if the value p is equal to or less than the level of significance α predefined, then the alternative hypothesis, which suggests a dependency between the variables, is accepted. Otherwise, the node is considered as the terminal node. The construction of the tree stops when the p-values of all observed independent variables are greater than a certain fractionation threshold. In the case of a quantitative dependent variable, an ANOVA F test is used to compare the means of the dependent variable for each of the categories of the explanatory variable used for the separation.

2. Merge the pairs of independent variable values that are the least different from the dependent variable. We use a distributional equivalence test of Khi-2 for this purpose. If the value p obtained is greater than a certain threshold of fusion, the algorithm merges particular categories without statistically significant differences.

3. Search for a new merge pair until the pairs, for which the value p is less than the defined level of significance α, are not identified.

In principle, because of the nature of data mining analysis, the application of the CHAID method requires the use of large samples.

Decision trees, and especially the CHAID method, have many advantages, including that they:

- are non-parametric; no assumptions on the distribution of the data are postulated
- can handle a large number of variables and they allow automatic selection of relevant variables
- can handle large volumes of heterogeneous data (categorical or numerical), resulting in reduced computing times
- are robust against outliers and offer a solution for missing data; input quality issues can be detected thus avoiding the construction of an invalid model based on poor quality data
- provide results that are visual and simple to interpret: the shape of a CHAID tree is intuitive, it can be expressed in the form of a set of explicit rules, in fact the paths summarising decisions transcribed in the form of rules (if ... therefore) are understandable and therefore easily interpretable
- are easy to integrate into existing IT processes due to their high level of automation and the ease of translating decision models into SQL for relational database deployment.

The contribution of this article is manifested by the application of the CHAID algorithm in the context of customs risk management in the detection of non-compliant revenue declarations.

4. Decision trees and the creation of customs risk profiles

4.1 Risk management and control channels

To deal with operational risks, the partner customs administration—like other customs administrations—is making efforts to improve its ability to target high-risk shipments. Indeed, this administration has two entities in charge of risk analysis: a private company that is the result of a public-private partnership and the Intelligence and Risk Analysis Service (SRAR). The private company uses a tool called Profiler, which is based on a scoring method to determine the risks, and then passes the profiles to the SRAR service that adds its own profiles for the purpose of transmitting them daily to the offices.

Regardless of the efficiency of the selectivity system of the partner customs administration, in this document we will use the CHAID algorithm to determine a predictive model to predict the 'revenue' risk associated with an import operation to detect risk factors and develop risk profiles.

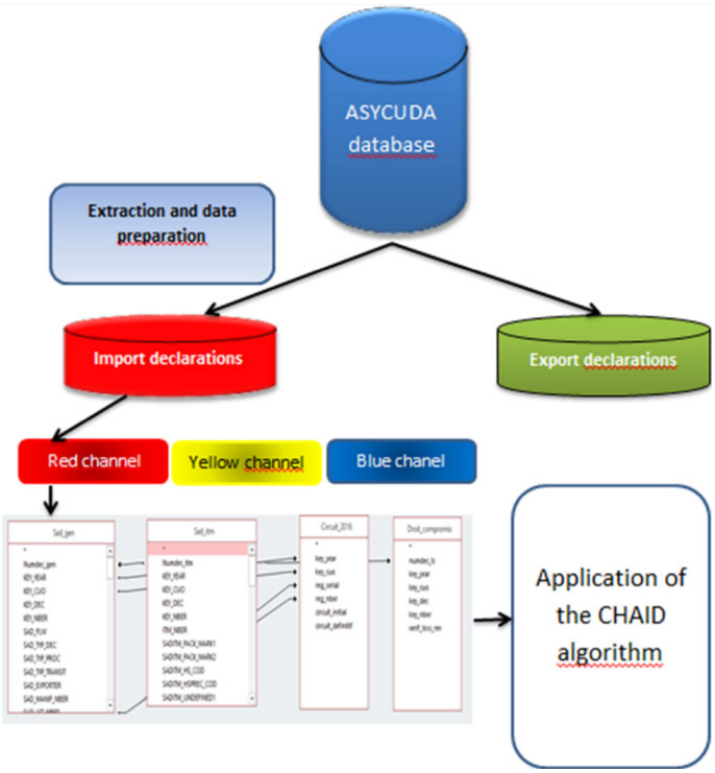
4.2 Modelling

To apply the CHAID procedure, we will present the data, variables, assumptions and specifications.

4.2.2 Data

The study was carried out with data extracted from the customs information system of the partner administration. We have established our study base on the import declarations registered in the partner customs clearance system for the year 2016.

Figure 4: Diagram of the flow of data



The first step is to select the data; this step decides what data will be used for the analysis. The data is collected in the form of four tables:

1. Sad_gen: Declaration header table
2. Sad_item: Table lines of declarations
3. Channel_2016: Declaration channels table
4. Laws_compromised: Laws compromised table.

The customs selectivity system of the partner administration, like that of many customs administrations around the world, directs all customs declarations to the blue, yellow or red channel. Import declarations in 2016 are set out in Table 1.

Table 1: Assignment of import declarations per channel

Channel	Number of declarations	Percentage %
Blue	31,494	25.31
Yellow	65,679	52.79
Red	27,253	21.90
Total	124,426	100.00

In our study, we will focus on the red channel as we have feedback on the compliance levels associated with these declarations because of physical inspections. It should be noted that the number of declarations found to be non-compliant within the red circuit is estimated at 1,440 declarations (5.28%).

4.2.2 Variables

The CHAID algorithm is developed on the basis of two groups of variables: the target variable (non-conforming declaration) and the predictor variables that will explain the target variable. These variables constitute the risk factors that may explain the non-conforming of a declaration.

Predictive variables or risk factors are presented Table 2.

Table 2: List of variables contained in the model

Variables	Type of variable
Reporting firm code	Chain
Consignee code	Chain
Type of customs procedure	Chain
Container (yes or no)	Chain
Customs procedure applied	Chain
Type of payment	Chain
Mode of transport	Chain
Delivery method	Chain
Active methods of transport	Chain
Last shipment country	Chain
Export country code	Chain
Nationality of the mode of transport	Chain
Place of unloading	Chain
Country of origin	Chain
Currency of invoice	Chain
Total value	Numerical
Total taxes	Numerical
Total gross weigh	Numerical
Total net weight	Numerical
Value by kilo of declaration	Numerical
Tax burden declaration	Numerical
HS2	Chain
HS4	Chain
HS6	Chain
HS8	Chain
Gross weight article	Numerical
Net weight article	Numerical
Value article	Numerical
Taxes per article	Numerical
Value per kilo of article	Numerical
Tax burden article	Numerical

4.2.3 Assumptions and specifications of the model

In the database received from the partner administration, several components related to the non-conforming of customs declarations are not communicated or are unavailable for reasons such as litigation or disputes.

This lack of information leads to the following assumptions:

H1. Any declaration that has been subject to an additional liquidation is deemed non-compliant.

H2. If a line of the declaration is found to be non-compliant, then all lines of the declaration are non-compliant and the additional amounts associated with this declaration count as many times as the lines of the declaration.

H3. A line of the declaration is treated as a declaration.

H4. The study covers all the import declarations oriented towards the red channel.

H5. A 10 per cent risk threshold is set in order to consider a declaration as non-compliant.

The specifications of the model are[1]:

S1. Number of observations per parent node is set at 1000 observations.

S2. Number of observations per child node is fixed at 500 observations.

S3. The Pearson Chi-square test is chosen and a common level of significance ($\alpha = 0.05$) for the division of the nodes and the merger of the categories of independent variables is determined.

S4. To evaluate the model we proceeded to cross-validation (k-fold cross-validation). We selected k =10 as a value, which is very common in the field of applied machine learning (Vercellis, 2009). Cross-validation consists of dividing the sample into k sub-samples of approximately the same size. The trees are generated by excluding the data from each sub-sample. The first tree is based on all observations except those in the first sub-sample, these data are the training samples and the sub-sample is the validation or test sample. The second tree is based on all observations, except those of the second sub-sample, and so on.

The overall accuracy is calculated as the arithmetic mean of k individual accuracies. The advantage of this method is that all observations are used for both learning and validation, and that each observation is used for validation precisely one time.

4.3 Results and interpretations

The results of the CHAID procedure (shown in Table 3 and Figure 6) indicate that the model created contains five levels of tree depth, for a total of 145 nodes, of which 99 are terminals. In addition, out of a total of 31 independent variables, the final model contains 15 variables, while the other variables are not statistically significant from a compliance perspective.

Table 3: Results

Total number of nodes	**145**
Number of terminal nodes	99
Depth	5
Number of variables included in the model	15

Figure 5: Overview of the decision tree

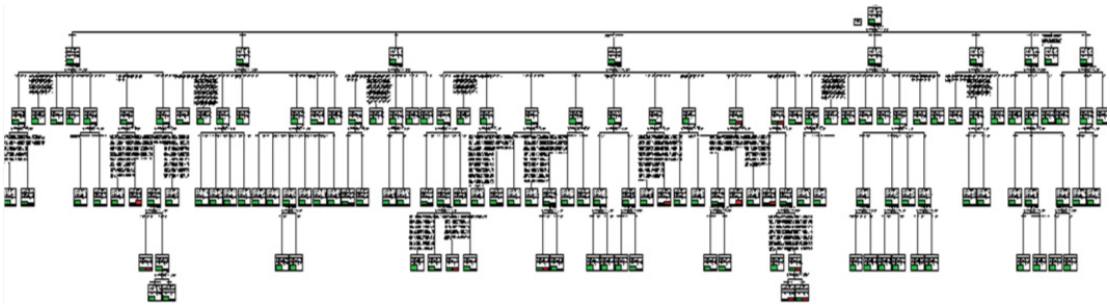


Figure 6: Root node

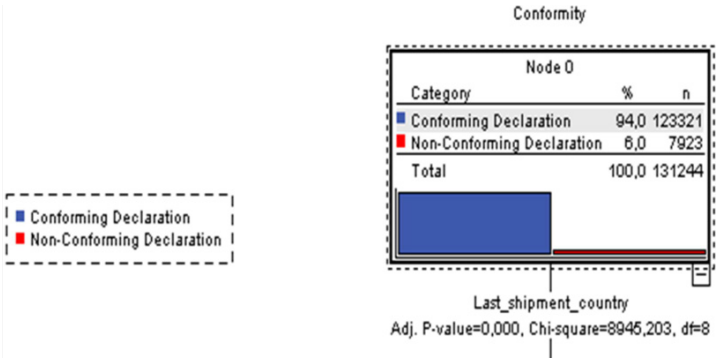
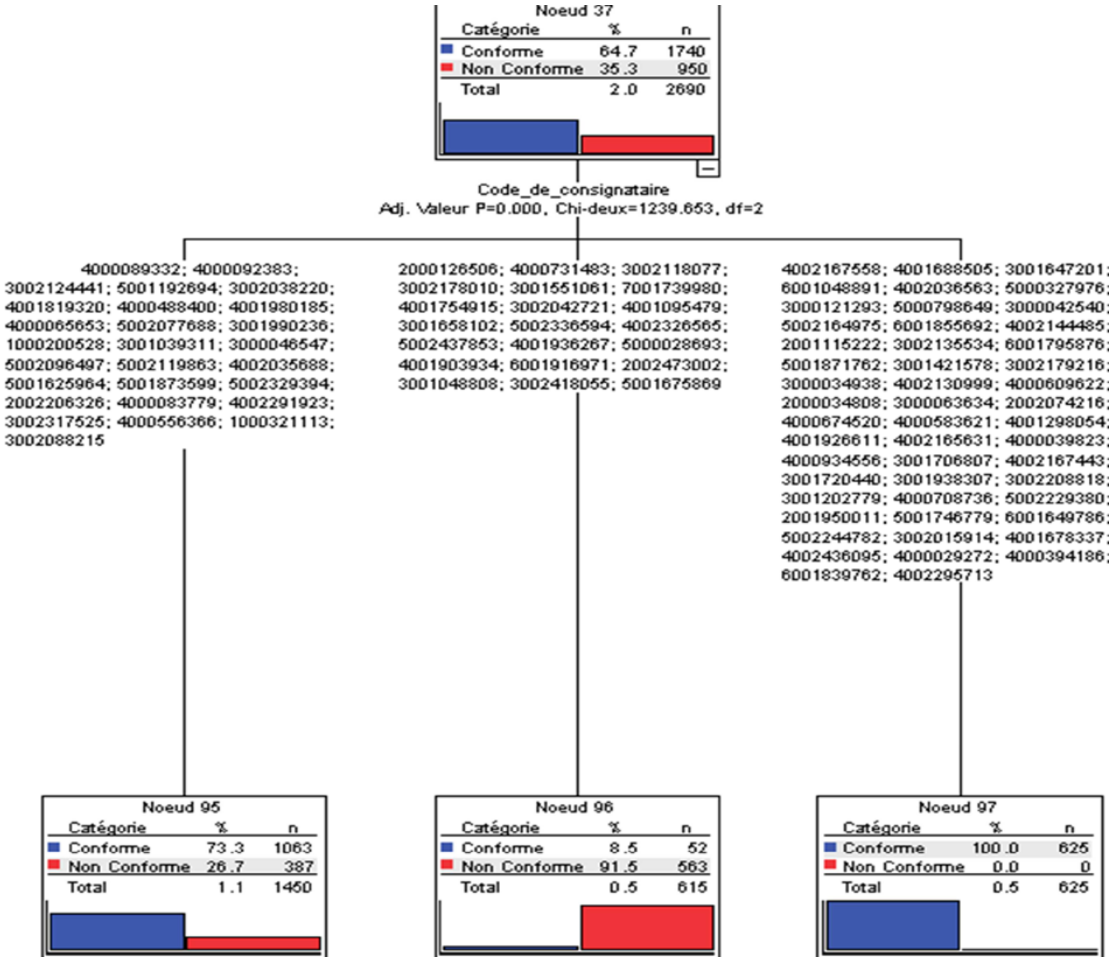


Figure 7 shows the root node that contains 131,244 lines of red-oriented declarations including 7923 non-conforming lines (6% of all lines).

Figure 7: Part of the decision tree



Referring to the decision tree, the last shipment country had the most significant effect on the conformance of a reporting line, which means that it is the variable most strongly associated with the dependent variable and that it has the most power in the division of observations into groups. In other words, for the observed data, this variable has the greatest potential to differentiate and classify the lines of clearance declarations into two groups (compliant and non-compliant), the statistical significance of the variable was determined, with $\alpha = 0.05$ using the following values: ($\chi 2 = 8945.203$, df = 8, p value = 0.000). As the first discriminator, it divides the root node, that is, a number of 131,244 declaration lines into eight groups containing different categories of the variable 'last shipment country'. The second-best predictor is the 'reporting firm code' for some parent nodes. The discrimination variables used, other than the variables mentioned above, are:

Consignee code	Country of origin	Total value
Net weight total	Method of payment	Article tax burden
Tax burden article	Nationality of the methods of transport	Article net weight
Mode of delivery	Customs procedure applied	Article value
Taxes per article	Declaration tax burden	

The table below (Table 4) shows the gain values that provide information about target categories (non-compliant reports). This table is only available if one or more target categories are specified. In our example, there is only one target category (non-compliant declaration). Only one gains table for the nodes is generated.

Table 4: Gains of the nodes

Node	Node		Gain		Response %	Index %
	N	Percentage %	N	Percentage %		
96	615	0.5	563	7.1	91.5	1516.4%
62	534	0.4	406	5.1	76.0	1259.4%
98	723	0.6	501	6.3	69.3	1147.9%
143	1,095	0.8	685	8.6	62.6	1036.3%
92	594	0.5	328	4.1	55.2	914.7%
. . .						
18	18,766	14.3	0	0.0	0.0	0.0%
41	7,560	5.8	0	0.0	0.0	0.0%
25	4,259	3.2	0	0.0	0.0	0.0%
94	4,045	3.1	0	0.0	0.0	0.0%
82	3,423	2.6	0	0.0	0.0	0.0%

The column 'Gain N' represents the number of observations in each terminal node of the target category. The gain percentage is the ratio of the number of observations of the target category to the total number of observations of this modality, namely the number and percentage of observations displaying the lines of non-conforming declarations in our study.

This table, therefore, contains all the terminal nodes. For each of the terminal nodes, there is a decision rule. A decision rule is an expression in the form 'If condition 1 ... Then ...'.

As indicated above, the terminal node 96 contains 615 lines of declarations, that is, 0.5 per cent of the total lines of declarations; the node 62 contains 534 lines.

The gain for node 96 is 563 lines of declarations, representing 7.1 per cent of all earnings and a response percentage of 91.5 per cent. The response percentage is calculated by dividing the gain by the total number of observations per node. This percentage is interpreted as follows:

- If a declaration line has the same characteristics of the lines belonging to node 96, then there is a 91.5 per cent probability that this line belongs to a non-conforming declaration.
- However, the node 18 contains 18,766 lines of the declarations, that is to say 14.3 per cent of the total lines of declarations, with a response rate equal to 0 per cent. Otherwise, the physical control of the declarations containing these lines of declarations did not result in anything.

The model development process is not complete until its performance has been evaluated. Tables 5 and 6 present basic information on the performance of the developed model in terms of accuracy and predictive potential.

Table 5: Risk (Response rate >=10%)

Method	Estimate	Standard error
Re-substitution	0.180	0.002
Cross validation	0.206	0.002

Table 6: Classification (Response rate >=10%)

Observed	Predicted		
	Conforming	Non Conforming	Percentage correct
Compliant	107,786	15,535	87.4%
Non-compliant	812	7,111	89.8%
Overall percentage	82.7%	17.3%	87.5%

The results in the classification table (Table 6) show that the model correctly ranks 87.5 per cent of the reporting lines, taking into account a risk ratio of 10 per cent.

- The percentage of correct classifications of the lines of the conforming declarations is equal to 87.4 per cent.
- The percentage of correct classifications of the lines of non-compliant declarations is equal to 89.8 per cent.

Table 5 presents the risk of prediction as a percentage of observations classified incorrectly. The risk estimate is 0.180; the risk of misclassification of a reporting line is approximately 18 per cent, while the average risk of misclassification using cross-validation is 20.6 per cent.

Note that the risk estimate and the overall correct classification rate are no longer moving in the same direction. With an overall correct classification rate of 87.5 per cent, the risk estimate should be 0.12—that is due to the cost of misclassifying high-risk declarations (10% risk ratio) that makes the interpretation less obvious.

In general, the best measure of the model's performance is not its raw accuracy, but its usefulness and effectiveness in achieving the main purpose for which it was created in order to solve a specific problem.

In addition, by grouping the lines by declaration, the model selects 16.70 per cent of the total import declarations directed toward a red channel to detect 80.35 per cent of the total non-conforming declarations in this channel.

However, by applying the model on all import declarations, the model targets 16,227 in total, including 11,072 from the yellow channel, 603 from the blue channel and 4,552 from the red channel, thus the physical control rate decreases from 21.90 per cent to 13.04 per cent.

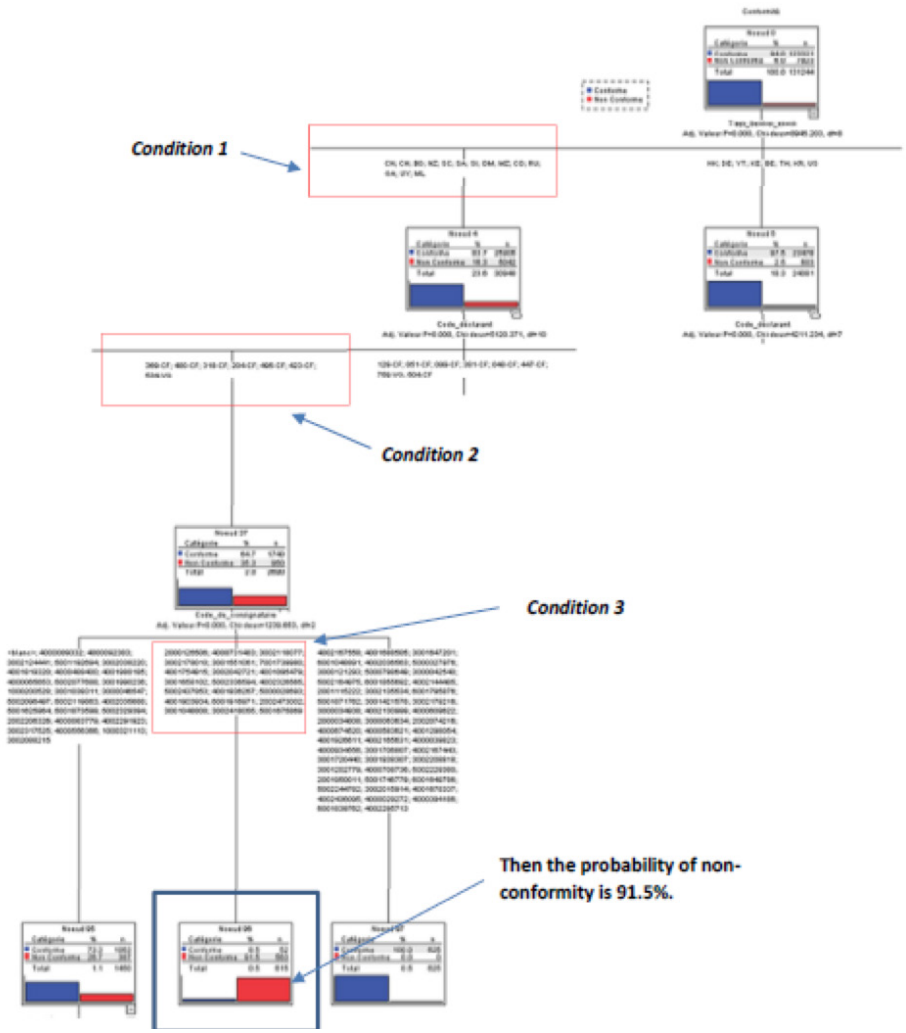
In terms of forecasting, considering a risk rate of 10 per cent, the number of targeting rules in this case is 32. Other rules that include terminal nodes can be used to direct declarations to other control channels (blue and yellow).

A problem may arise in the case where a declaration is unclassified, then it may be considered because of a lack of prior information. 'IF' rule 1 'OTHERWISE' rule 2 'OTHERWISE' rule 3 '... OTHERWISE classified by default (red channel)'.

4. 4 Creation of risk profiles

The paths of a decision tree are represented as 'if-then' rules. For example, 'if condition 1 and condition 2... and condition k occur, then result j occurs'. This is illustrated in Figure 8.

Figure 8: Example that shows how a rule from the decision tree is interpreted

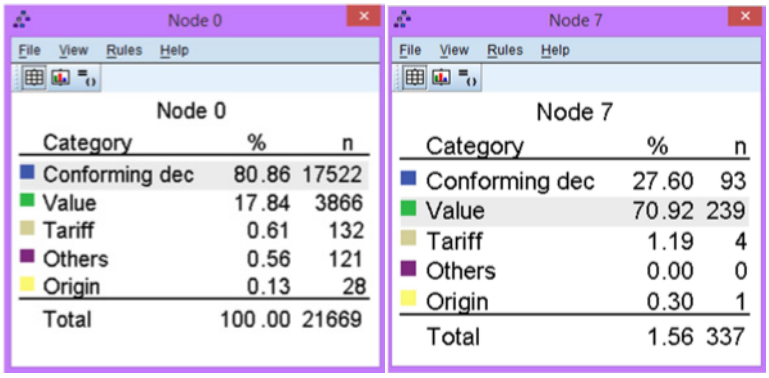


As mentioned in the previous section, reading the decision tree is easy. Indeed, a simple vertical reading of the tree going from the root node to the terminal node allows for rules to be extracted, as shown in the Figure 8 above.

The rules can be translated as SQL instructions and can easily be entered into the customs clearance system.[2] Appendix A provides an example of the way the rules or risk profiles can be written.

Moreover, the CHAID method's ability to generate non-binary trees is particularly interesting. Risk profiles can be determined depending on the nature of the offence, and of course depending on the information available in customs databases, as shown in Figure 9.

Figure 9: Example risk profiles



5. Conclusion

In this paper, we presented a supervised learning method and applied it to customs data. We used the CHAID algorithm to develop a risk model.

This method is considered among the best techniques for creating visual and easily interpretable models, allowing for the establishment of a series of rules, and consequently creating risk profiles and classifying customs declarations of goods using such profiles.

We sought to extract the most relevant risk factors, such as the country of last shipment and the declarant, evaluated the model by the classical 'cross-validation' method, and showed how easy it is to derive rules from the results obtained.

The application of this algorithm can be extended to solve other problems. However, this decision tree method does contain some limitations, sometimes related to the large number of categories that renders them complex and illegible. Furthermore, it is very difficult to identify an optimal decision tree.

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Notes

1 We used the SPSS V 21.00 programme, which allows for the implementation of a decision tress process—the CHAID method. However, it is also possible to use open source software such as R or Python.

2 SPSS software enables the extraction of rules in the form of SQL instructions.

Appendix A

```
/* Node 96 */
                UPDATE <TABLE targeting>
                '       SET nod_001 = 96,       pre_001 = 1,prb_001 = 0.915


SELECT * FROM <TABLE>
WHERE ((((((((((((((Last shipment country = "CN") OR (Last shipment country = "CH")) OR (Last shipment
country = "BD")) OR (Last shipment country = "NZ")) OR (Last shipment country = "SC")) OR (Last shipment
country = "SA")) OR (Last shipment country = "SI")) OR (Last shipment country = "OM")) OR (Last shipment
country = "MZ")) OR (Last shipment country = "CO")) OR (Last shipment country = "RU")) OR (Last shipment
country = "GA")) OR (Last shipment country = "UY")) OR (Last shipment country = "ML")) AND
(((((((Reporting firm code = "369-CF") OR (Reporting firm code = "480-CF")) OR (Reporting firm code =
"318-CF")) OR (Reporting firm code = "204-CF")) OR (Reporting firm code = "495-CF")) OR (Reporting firm
code = "423-CF")) OR (Reporting firm code = "534-VG")) AND ((((((((((((((((((((Consignee code =
"2000126506") OR (Consignee code = "4000731483")) OR (Consignee code = "3002118077")) OR
(Consignee code = "3002178010")) OR (Consignee code = "3001551061")) OR (Consignee code =
"7001739980")) OR (Consignee code = "4001754915")) OR (Consignee code = "3002042721")) OR
(Consignee code = "4001095479")) OR (Consignee code = "3001658102")) OR (Consignee code =
"5002336594")) OR (Consignee code = "4002326565")) OR (Consignee code = "5002437853")) OR
(Consignee code = "4001936267")) OR (Consignee code = "5000028693")) OR (Consignee code =
"4001903934")) OR (Consignee code = "6001916971")) OR (Consignee code = "2002473002")) OR
(Consignee code = "3001048808")) OR (Consignee code = "3002418055")) OR (Consignee code =
"5001675869"))));
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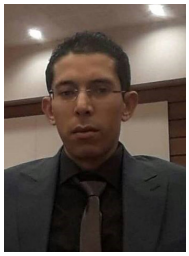
Bassem Chermiti



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Identifying trade mis-invoicing through customs data analysis

Yeon Soo Choi

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.

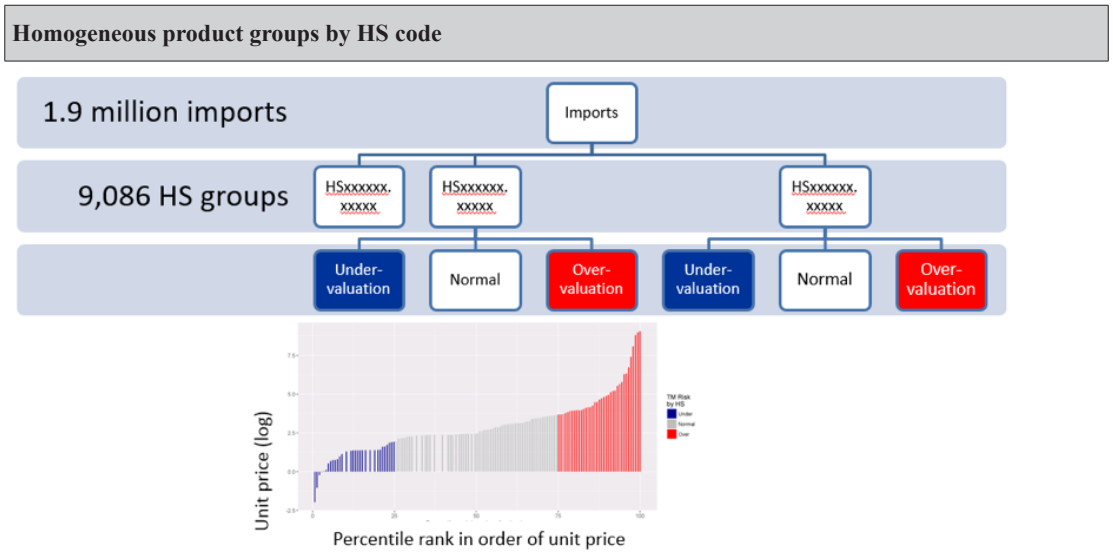
3.2 Homogeneous product groups

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

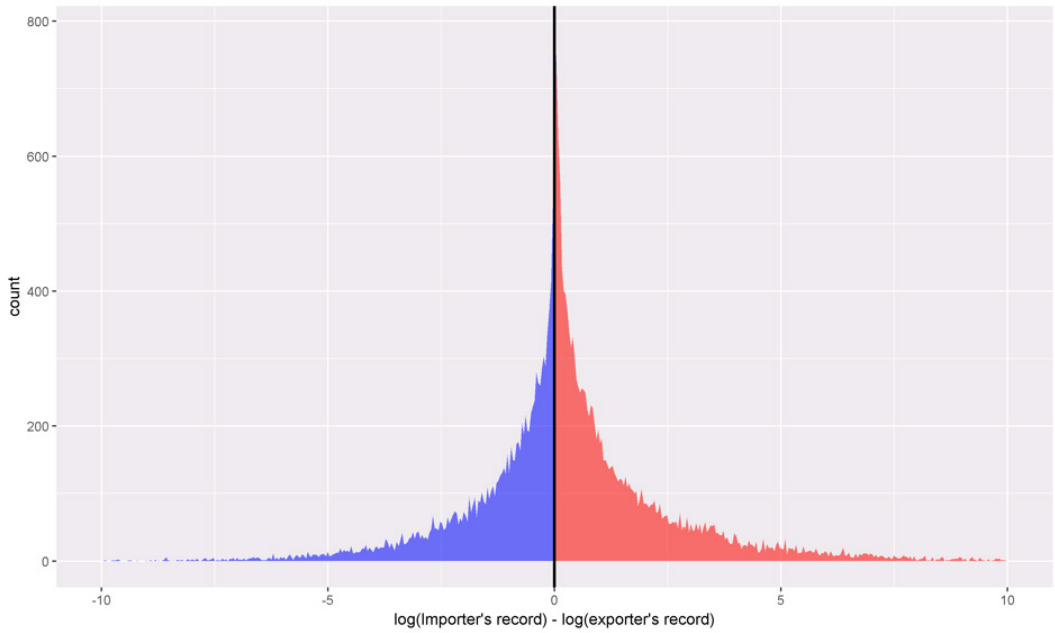
Every trade transaction has two records, one recorded by an importing country (importer's value) and the other recorded by an exporting country (exporter's value). While there are several legitimate or statistical reasons that may explain any gap between two trade records, if the gap is significantly 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)

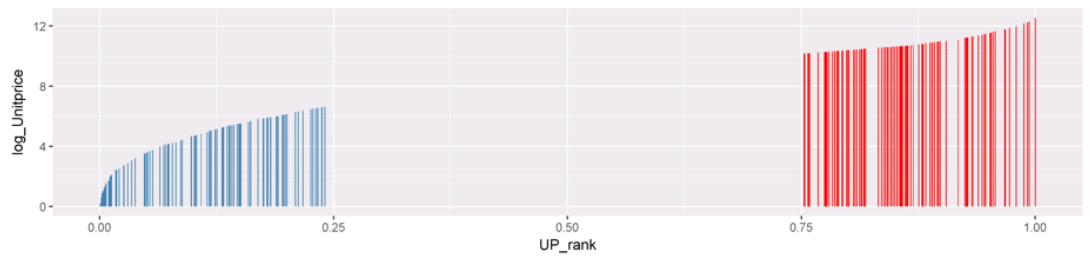
Risk area	Targeting methodology	Inspection[8] (cases)	Inspection rate %	Actually illicit (cases)	Targeting accuracy %
Unknown	Red-channel	532,127	27	66,463	12
Under-valuation	PFM & PCM	34,975	2	6,412	18
	PFM & PCM in Red-channel	16,462	1	5,963	36
Over-valuation	PFM & PCM	92,232	5	1,287	1
	PFM & PCM in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

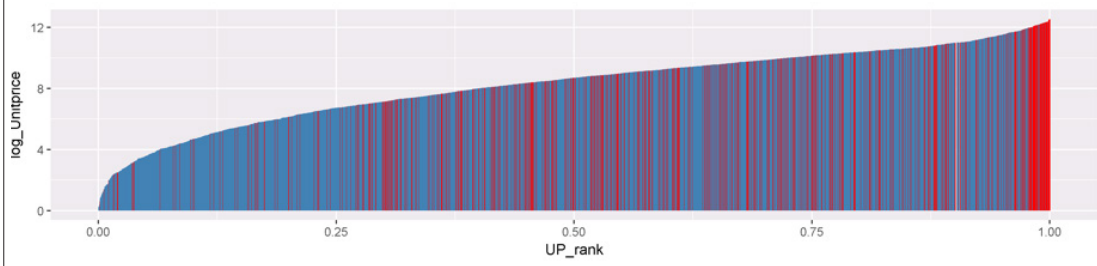
Figure 3 outlines how suspicious imports were identified using a step-by-step process and a sample of 2,875 imports under HS 540752.xxxxx. All the imports were listed in order of unit prices, and the height of each bar represents its unit price (logged value). Imports suspected of under-valuation were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

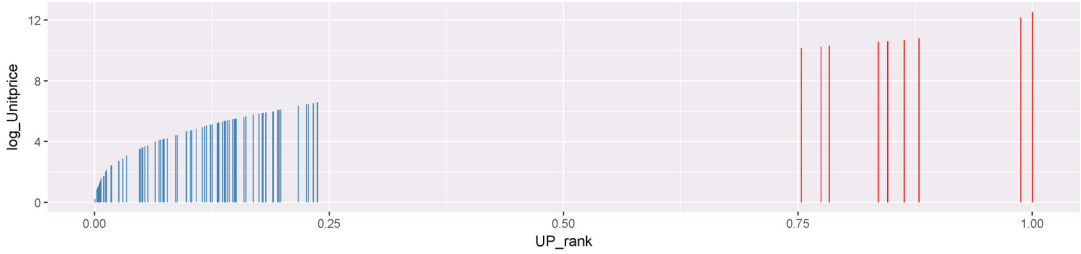
1st step: Price Filter Method (Unit Price Analysis)



2nd step: PCM

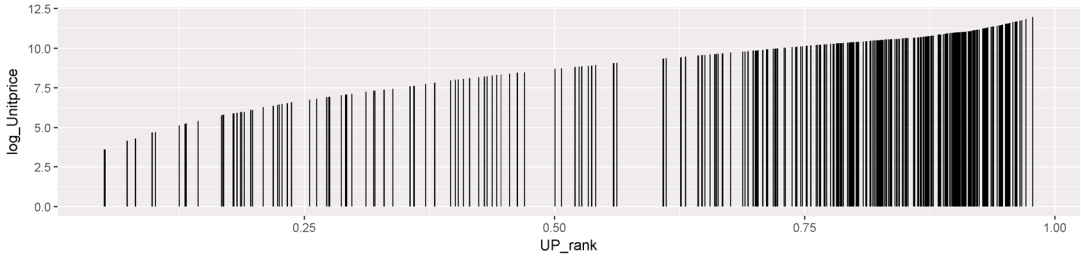


3rd step: Cross-reference PFM and PCM

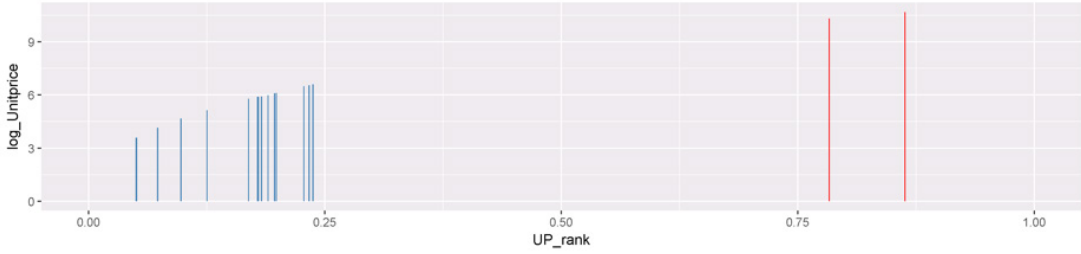


4th step: Verification

<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

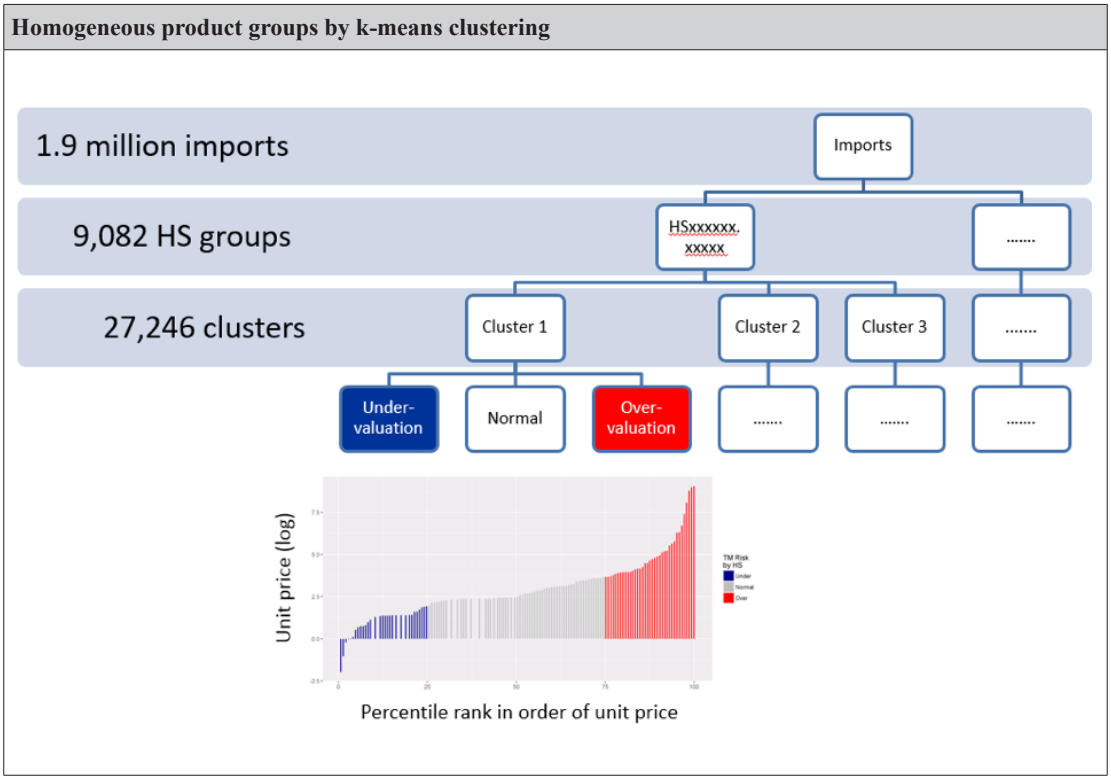
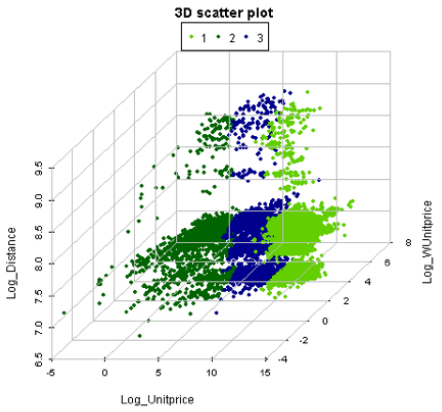


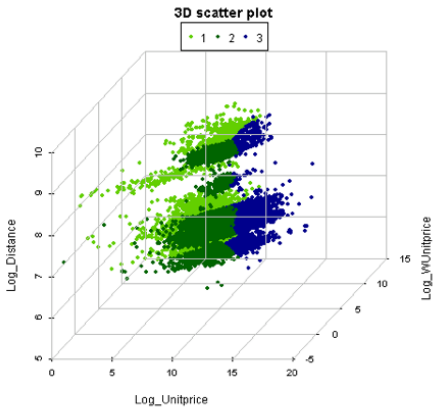
Figure 5. Examples of the formation of homogeneous product groups

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



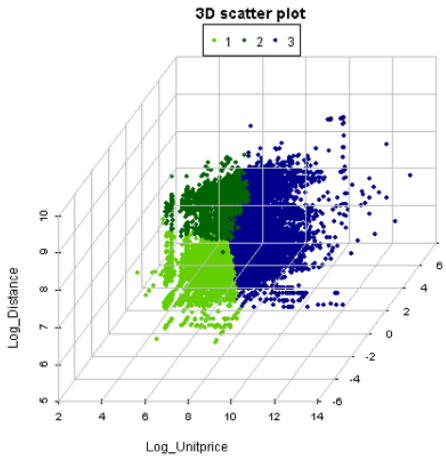
Cluster	Size (number of imports)	Cluster center		
		Unit price (log)	Weight price (log)	Distance (log)
1 (light green)	2,434	3.3	1.7	7.5
2 (dark green)	3,978	7.3	3.3	7.3
3 (blue)	5,883	10.5	3.2	7.3
Total	12,295	–	–	–

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)

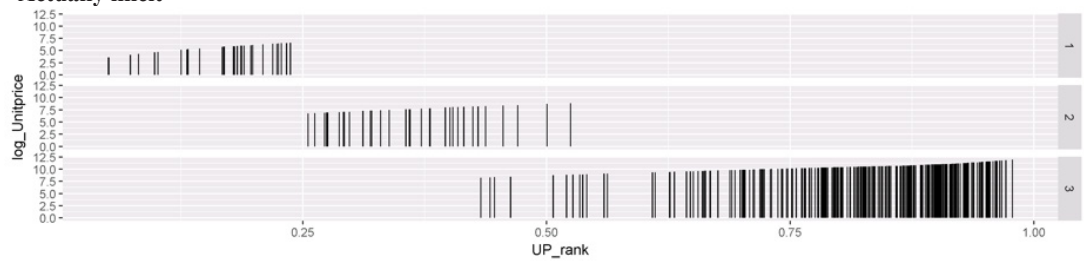
Risk area	Targeting methodology	Inspection (cases)	Inspection rate %	Actually illicit (cases)	Targeting accuracy %
Overall	Red-channel	532,127	27	66,463	12
Under-valuation	PFM & PCM	26,924	1	4,337	16
	PFM & PCM in Red-channel	12,018	0.6	3,896	32
Over-valuation	PFM & PCM	88,517	5	1,866	2
	PFM & PCM in 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.

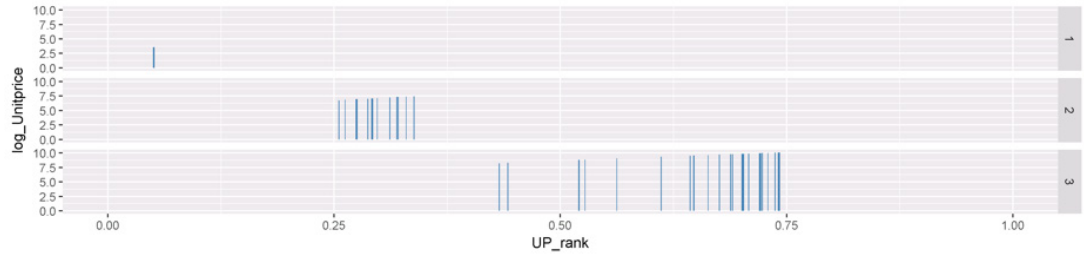
Figure 6. Process of identifying suspicious transactions and verification with clustering (Example of HS 540752.xxxxx)

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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Revenue maximisation versus trade facilitation: the contribution of automated risk management

Christopher Grigoriou

Abstract

Customs administrations in developing economies are most frequently confronted by two seemingly mutually exclusive objectives: revenue maximisation and trade facilitation. The goal of maximising revenue most often implies a strengthening of customs controls, while trade facilitation suggests a more rapid release of goods.

This paper demonstrates that, by using targeting techniques based on the calculation of a score derived from results of previous controls, these two objectives can be reconciled.

The simulations presented are formulated on one year of anonymous customs declarations and modelled accordingly. The results show that: (1) the volume of control-oriented declarations can be drastically reduced by only slightly impacting the results with regard to offences detected: 80 per cent of offences could have been detected by focusing on just 30 per cent of the declarations that had been identified as high risk (i.e. with the highest score); and (2) simulations suggest that the use of this type of targeting techniques would have drastically increased (up to 100 per cent) the volume of offences recorded by targeting declarations that did not undergo a physical examination in place of targeted declarations without a conclusive result.

1. Introduction

1.1 Control more to maximise revenue or control less to facilitate trade?

Customs administrations are at the centre of multiple challenges and are at the crossroads of issues of migration, security and trade facilitation, and the collection of state revenue. Many developing economies that have not yet completed their fiscal transition still derive a large portion of revenue from Customs—mainly customs duties and value added tax (VAT).

Many customs administrations that have revenue maximisation as a priority have been observed directing a high rate of declarations towards a control channel, despite operating in a context of scarce resources with limited human capacity to carry out these controls. The result is a *lose-lose* system that culminates in neither trade facilitation nor revenue maximisation. The high volume of declarations directed towards a control channel, most often resulting in a relatively small number of actual offences, is irrelevant, due to a lack of objective targeting. It is impossible, and counterproductive, for Customs to inspect and verify each transaction and such a practice would entail additional costs for economic operators. Moreover, the opportunity cost involved in inspections is considerable. The elaborate control mechanisms that are required for even compliant importers monopolise the resources and time of inspectors and diverts

their attention away from *actual* high-risk transactions. Furthermore, the practical impossibility of verifying high volumes of declarations implies that the selection made by inspectors regarding high risk declarations that will be actually controlled will potentially be an arbitrary one.

The adoption of practices based on automated risk analysis reverses this situation for customs administrations by providing an effective solution to the trade-off between controlling more, to ensure that all declarations are compliant and fulfil the goal of maximising revenue, and controlling less, to promote trade and to avoid being perceived as an 'obstacle' to trade.

The procedure governing risk analysis techniques ensures that high-risk declarations that are suspected of being non-compliant are identified and targeted and that physical inspections are concentrated where they are needed most. Targeting controls in this manner implies a mechanical reduction in the opportunity cost of inspections, and an increase in the efficiency of staff. Customs administrations that have adopted such techniques have seen the benefits accumulate in both the public and private sectors. Risk analysis is therefore an extremely useful tool for customs administrations in the process of modernisation.

2. Analytical framework

2.1 Principles of risk analysis with regard to the selectivity of controls

2.1.1 Implementation of a risk management system: World Customs Organization (WCO) framework

WCO recommendations for the implementation of a risk management system comprises five steps:

1. establishing the context
2. identification of risks
3. analysis of the risks
4. evaluation and prioritisation of risks
5. treatment and evaluation (see WCO, 2003, among others).

Each step feeds into and fuels the next. Implementation of this type of framework can take time, considering the practical reform that is fundamental to its success, particularly with regard to the level of transparency and governance required to obtain a database with results from controls that is reliable, continuously updated and operational.

Risk-based evaluation processes ensure that each declaration is categorised into a control channel that corresponds with its risk profile. This step is linked to an estimation of the probability of non-compliance, which is based on the previous history of each of the declarations' elements (i.e. whether it was associated with fraud cases in the past). This type of risk targeting, based on estimated levels of risk, ensures that priority is accorded to the riskiest transactions, thereby providing for a more efficient resource allocation system. Risk management, therefore, not only categorises and selects high-risk declarations, but improves the efficiency of services by optimising the allocation of resources and modernising administrative structures through the use of new technologies.

2.1.2 Implementation of a risk management system: an incentive to comply

Risk management is in and of itself an incentive for compliance. In the context of a principal–agent relationship characterised by an information asymmetry, Alm, Bahl and Murray (1993) and Alm, Cronshaw and McKee (1993) show that importers with low-risk profiles are strategically incentivised to become compliant. Risk management practices have an inevitable impact on all economic operators through detections, inspections and the sanctions—penalties or destruction of merchandise—that result, and all the more so considering that the controls are focused on high-risk declarations. Furthermore, risk

management techniques furnish information—a source of economic intelligence—and activity reports that enable administrations to evaluate the effectiveness of its inspection services. Finally, given the lack of cooperation often observed between the public and private sectors, inspections provide an opportunity for an administration to remind importers of their legal obligations.

2.1.3 Risk analysis: from risk evaluation to risk profiling

The procedure used for profiling a transaction must be based on a standardised and objective methodology to avoid arbitrary decisions basely solely on the whim of an individual, and to avoid possible collusion and corruption. Conversely, given the evolving nature of world trade, risk management practices must be dynamic and scalable. As noted above, a consistent and well-structured risk management framework provides incentives for economic operators and influences their behaviour. The procedure underlying the elaboration of risk profiles must not be decodable by economic operators; they must not be given any opportunity to circumvent the rules. Finally, risk management systems must be implemented using computerised processes, in accordance with the Revised Kyoto Convention and the recommendations of international institutions on the modernisation of border control practices using standardised, non-intrusive methods.

2.1.4 The pillars of risk analysis for Customs selectivity controls

Customs administrations operate with systems that can be highly advanced or rudimentary, depending on their degree of modernisation; between selective 'blocking rules' based on Customs intelligence, risk-based predictive analysis, and simple random selectivity.

Customs intelligence

The customs intelligence service occupies an important position in the risk management information chain; the system is fed information sourced from the Customs investigation services or from various inter-Customs collaborations, which allow, before a declaration is even filed, a control plan to be put in place in accordance with the origin, importer or tariff heading, previously identified as being 'at risk'. Selectivity 'blocking rules', which will determine the categorisation of future declarations, then come into play. In practice, these rules are based not only on customs intelligence but also on the accumulated experience of inspectors with the behaviour of importers and economic operators. Special attention may thus be paid to imports from countries A and B, or to imports of particular products, which will then be considered on a blanket basis to be high risk.[1]

While this approach may seem appealing due to the apparent ease of implementation and low levels of data and/or information required, its limits are substantial:

1. the risk of collusion or corruption between importers and inspectors is increased as they each have access to information on the criteria used to categorise goods—criteria which moreover can be, at least partially, arbitrary
2. the criteria used to assess 'high-risk' declarations can be decoded and therefore be revealed to non-compliant traders
3. the system is not sufficiently dynamic as the blocking rules are, by definition, static, whereas non-compliant importers will adapt their behaviour in real time in accordance with the control strategies put in place.

Combined, these disadvantages significantly limit the appeal and benefits of this approach. It is not uncommon for tariff headings or countries of origin to 'disappear' from declarations when they are targeted for systematic checks and to 'reappear' when the corresponding blocking rules are removed. Despite these limitations, it is interesting to use these blocking rules when particular information on a cargo or economic operator originates from investigation services or a collaboration between customs services, but these rules must be defined frequently and be applied for a fixed period only.

Predictive analysis

The scope of investigation of Customs-based, 'qualitative' intelligence targeting is inherently limited; however, it is complemented by a 'quantitative' analysis based on a comprehensive examination of database history, often significant in size and featuring several hundred thousands, if not millions, of observations, concerning both past customs declarations and the results of the associated controls.

Modern administrations have progressively developed and implemented predictive approaches to profiling, targeting and inspecting non-compliant declarations to supplement intelligence-based selectivity. This approach is an integral part of modernisation programs for administrations in developing and transition countries (see, for example, Widdowson, 2005). Furthermore, it makes it possible to ensure that the majority of inspection resources are focused on declarations with a high (risk) score (see Geourjon & Laporte, 2005, or Grigoriou, 2012, for an application of risk analysis in the context of non-tariff measures, such as sanitary or phytosanitary, or technical standards).

Each declaration is assigned a score in accordance with the background information associated with the various elements of the declaration (country of origin, importer, tariff classification, etc.). This risk profiling is dynamic as the profiles are updated continuously and can integrate any new information or trend change. In addition, the calculation of scores using an objective scientific approach ensures that rules are non-abitrary and non-decodable by economic operators.

The declarations are then directed toward the control channel in accordance with their risk categorisation, evaluated on the calculation of their score, likened to a probability of non-compliance. This predictive analysis goes hand-in-hand with customs intelligence because it relies on a comprehensive and panoramic view of customs offences as identified by customs services. Moreover, this predictive analysis, based on the estimation of a risk of fraud, guarantees a procedure based on selective controls in accordance with the revised Kyoto Convention because of its objective (non-arbitrary) and standardised, dynamic, scalable and adaptable characteristics.

This predictive approach can and must therefore be combined with customs intelligence to enable the risk management system to incorporate information procured from the intelligence services; the incorporation of this 'random rule' completes the system. This approach, randomly redirecting a percentage of the declarations identified as low risk at a predefined rate, ensures regular supervision of all operators and encourages compliant importers to remain so.

A random rule

The 'random rule' supplements targeting based on a combination of customs intelligence and predictive analysis. The 'random rule' corresponds to a random reallocation of low risk declarations toward physical inspection of the goods. Naturally, this method does not require a particularly developed IT infrastructure and ensures that importers are treated fairly. Since the probability of being randomly selected is the same for all importers, the risk of corruption and arbitrary selectivity are substantially reduced, on condition that the random selections are indeed 'random'. This rule also provides an incentive to importers to remain compliant, as they are all susceptible to be directed toward a control channel.

This last point runs counter to the principle of blocking rules, which would never select an importer that had been categorised as compliant during past inspections. Finally, random selection makes it possible to detect new types of offences as it results in controlling goods that wouldn't have been targeted otherwise.

However, this method is obviously only a complement to the former ones as it has significant limitations:

- it is not dynamic
- the random nature of it precludes any opportunity to capitalise on information from past controls and fraud and/or compliance trends.
- the opportunity cost associated with controls can be very high as medium-risk declarations will have the same probability of being selected as low-risk declarations, leading to an inefficient allocation of resources.

Nevertheless, this approach remains relevant and useful to complement targeting based on a combination of customs intelligence and predictive analysis as it ensures that any declarations can be verified.

3. The mechanics of predictive analysis: the econometric evaluation of risk profiles

3.1 The data, the model

The raw material contained in any risk analysis system consists of results of past controls. The database containing the result of the verifications should highlight all the principle characteristics of the declarations, such as importers' codes, HS codes and country of origin, as well as the results obtained during the physical control of the commodity. This database must be continuously updated to reflect possible changes in the behaviour of economic operators. Consequently, the first step is to build such a database if it has not already been incorporated into the administration's IT system.

Once the database has been created, the model that will be used to estimate the risk profiles of the declarations can be defined. The dependent variable is the rate of non-compliance observed. This variable can be discrete or continuous. The explanatory variables are the criteria scores, that is, the elements of the declaration (e.g. the country of origin, the HS code) that will be used to predict fraud. Scores are calculated for each element of the declaration according to the priorities of the administration in charge of the conformity analysis. These scores reflect the risk profile that is composed of an amalgamation of the history of these compliance criteria. For example, the scores attributed to each country of origin will be higher if these countries have ever been associated with non-compliant declarations. The results of the new checks then feed into the database, along with the criteria scores, allowing a dynamic adjustment of the system.

3.2 The contribution of econometrics in estimating the risk profile of declarations

The assessment of the risk profiles of the declarations is based on the econometric analysis of the offences. The econometric analysis identifies the elements of the declaration, called criteria, which are relevant to estimate the risk profiles of the declarations. These elements are considered as significant predictors of fraud when their scores are highly correlated with the extent of fraud. These criteria are then used to estimate the risk profile of a new declaration. Finally, the set of criteria scores are aggregated in a single overall score from the estimated coefficients inherited from the econometric model estimates. The single overall score, that is, the score of the declaration determines directly the risk profile of the declaration; the higher the score, the riskier the profile.

Econometrics also allows for different approaches depending on the quality and granularity of the data as well as the types of fraud encountered. These approaches may be linear or non-linear, depending on the type of non-compliance to be modelled, with the potential consideration of individual or time-specific effects if the data collected allows for panel data analysis.

Once the econometric regression has been performed, each new declaration will have a risk profile based on the set of scores of the elements on the declaration that have previously been identified as relevant to predict non-compliance.

It should be remembered that while risk-based analysis is at the heart of the system, the use of intelligence-based blocking rules and a low percentage of random selections is an integral part of the system; the first allows the assimilation of specific information, the second encourages compliant importers to remain so.

3.3 Contingency table and monitoring the effectiveness of the model

Econometrics ensures that systems go 'beyond the black box' and highlights the relationship (causality) between the observed offences and each criterion, as well as the overall contribution of each criterion to the elaboration of the risk profiles. All data collected and estimated serve as a basis for monitoring and evaluating the selectivity of the system controls, including criteria scores and predictions. The performance and consistency of the system is then evaluated from contingency tables. This evaluation is crucial in that it evaluates the accuracy of the model and adds value to existing methodologies governing risk management.

Table 1 matches for a given period the actually observed conformity of offence versus what had been initially predicted. The type 1 and 2 errors are respectively clearing a fraudulent declaration (false negative), or controlling a compliant declaration (false positive). The percentage of accurate predictions includes true negative and true positive, itself a measure of the accuracy of the model.

Table 1: Contingency table

		Prediction	
		Conformity	**Offence**
Observation	Conformity	True negative	False positive
	Offrence	False negative	True positive

This table defines the efficiency and relevance of the model. The prediction efficiency score is the percentage of actual non-compliant declarations that were targeted as such by the model. The relevance score measures the percentage of reports targeted as non-compliant and which were revealed to be non-compliant. The de facto result is a compromise between these two indicators. Since the efficiency rate implies an increase in the number of controls, it mechanically induces a decrease in the relevance score and vice versa (see Gupta et al., 2007). Conversely, increasing the relevance score implies a reduction in the number of inspections in an effort to reduce the number of false positives, which can in turn lead to a reduction in the efficiency score.

4. Application

This section illustrates the benefits of a predictive analytics-based methodology for targeting declarations that require physical inspection, thereby optimising inspections. The simulations presented here are based on a real but anonymised dataset (for confidentiality).

4.1 Presentation of the data

The following exercise concerns customs clearance anonymised data spanning a full year and covering 300,000 declarations released for consumption. Approximately half of these were directed through physical control channels, of which 5 per cent were associated with the detection of an offence, which is consistent with the levels observed in many customs administrations of developing economies.

The elements to be considered as potentially predictive criteria for targeting the declarations to be inspected are the following[2]:

1. HS (Harmonized System – international nomenclature for the classification of goods) codes: there are over 10,000 different products contained in this database
2. trading partners: 170 countries of origin
3. importers: 4,000 importer-specific identification numbers
4. freight forwarders: 150
5. the ports of entry: 50 different sites are considered here as potential points of entry into the country
6. the type of activity: 500.

The description and the inventory of the different modalities of each criterion are presented in Table 2. The global masses have been slightly modified compared to the 'real' data in order to preserve the anonymity of the customs administration in question.

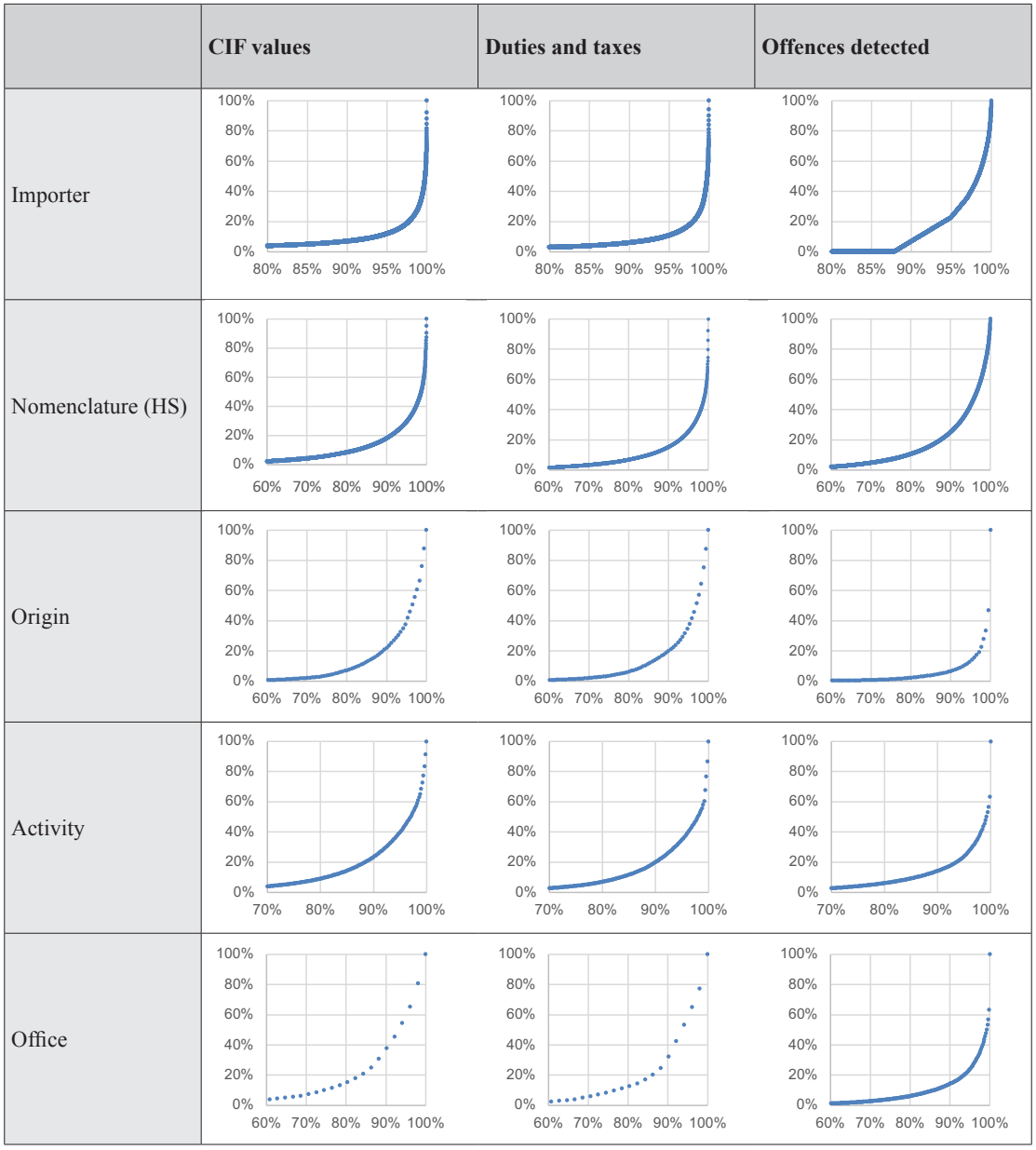
Table 2: Criteria for predicting fraud – 100,000 observations

Criterion	# of modalities	Description of criteria
HS Code SH	10,000	Classification HS6
Country of origin	130	Country of origin
Importer	4,000	Identification number
Port of entry	50	Port (office) of entry
Freight forwarder	150	Freight forwarder ID
Activity	500	Type of activity

Figure 1, below, outlines the concentration of imports, associated duties and taxes, and offences, organised by criterion. Each graph represents, on the vertical axis: the cumulative frequency of imported values, Cost Insurance Freight (CIF) price, and duties and taxes collected by Customs. Offences detected in accordance with the cumulative frequency of the criterion selected (e.g. percentage of importers, nomenclatures, origins) are represented on the horizontal axis.

As an example, operations are concentrated among a small number of importers, since 1 per cent of importers alone account for 70 per cent of imports (by value), 72 per cent of duties and taxes collected by Customs, and close to 40 per cent of offences.

Figure 1: Concentration of imports, duties and taxes and offence by criterion
(per cent of cumulated frequencies)



Source: Calculations made by the author using anonymised Customs data.

4.2 The modelling: qualitative dependent variable model

Logit and probit estimators are specifically designed for binary-dependent variable models. The objective here is to model the probability that the variable Y will take the value 1 (offence). It is common to adopt a non-linear approach so that the predicted value is always between 0 and 1. Distribution functions are then used for such non-linear estimators of logit or probit type, because they provide by definition probabilities included in 0 and 1. In this case, the distribution function of the normal rule with respect to

the probit estimator is used. The estimate is then based on the maximum-likelihood method to maximise the probability of correctly predicting the dependent variable.[3]

The binary dependent variable retraces two situations, the probability of occurrence for which will be evaluated. The objective is to assess the likelihood of a new declaration being non-compliant. The regression to estimate in probit is as follows:

$P(Y = 1/X_1, X_2, \ldots, X_n) = \Phi(\beta_0 + \beta_1.X_1 + \beta_2.X_2 + \ldots + \beta_n.X_n)$

P(Y = 1) is the probability that the declaration is non-compliant, Φ is the distribution function of the normal rule. $X_{1i}, X_{2i}, \ldots, X_{ni}$ are scores of the associated modality criteria as set out in Section 3.

$X_{1i}, X_{2i}, X_{3i}, X_{4i}, X_{5i}, X_{6i}, X_{7i}$, represent respectively scores of the HS codes, countries of origin, importers, final destination, port of entry, packaging, and the declaration's freight forwarder (for good i). Finally, β_1, $\beta_2 \ldots \beta_n$ are the parameters to be estimated. These parameters reflect the impact of an increase in X (the score of the particular modality criteria) on the probability of non-conformity.

4.3 The regression

Table 4 presents the results of the estimations.

Table 4: Scores of the criteria and probability of offence
Probit estimate, January–June 2016

Binary dependent variable	**Offence**
Importer	5.48*** (0.032)
Nomenclature	1.19*** (0.05)
Origin	1.8*** (0.08)
Port of entry	0.97*** (0.068)
Activity	0.72*** (0.66)
Constant	–4.18*** (0.019)
Obs	250,000
Estimator	Probit
Maximum Likelihood	16,004
Pseudo-R2	0.55
*** for a coefficient significant at 1 per cent with robust standard errors	

This regression provides four types of information for risk management:

1. It provides information on the criteria that are statistically significant predictors of fraud, that is, the criteria that must be used to calculate the probability of fraud of a given declaration. For these criteria, the probability of fraud will be increasing with the scores of modalities. It appears from Table 4 that the importer, nomenclature, origin, port of entry and activity are good predictors of fraud.
2. The regression provides the weights to be used to calculate the overall probability of fraud of the declaration, aggregating the set of criteria scores.
3. A contingency table (see Table 5 below) is derived from the econometric estimates to assess the quality of the predictions. By comparing the proven non-conformities to the model's predictions, in other words by comparing the 0s and 1s predicted to the 0s and 1s observed, the following contingency table can be calculated, highlighting the quality of the predictions.

Table 5: Contingency table

'Proven' fraud	**Predicted fraud**		**Total %**
	0 %	**1 %**	
0	85.8	3.4	89.2
1	2.2	8.6	10.8
Total	**88.0**	**12.0**	**100.0**

NB: figures are presented in relative value to preserve confidentiality.

The contingency table (Table 5) can be used as a basis for assessing the quality of the model. The overall accuracy of the model is such that almost 94 per cent of the referrals are correct. In addition, by plotting the number of true positives (8.6 per cent) with the total number of non-compliant reports (10.8 per cent), an estimate of the effectiveness is obtained of 80 per cent. Finally, the rate of relevance defined as the number of true positives (8.6 per cent) on the projections of non-compliance (10.8 per cent) is 72 per cent.

4.4 Simulations

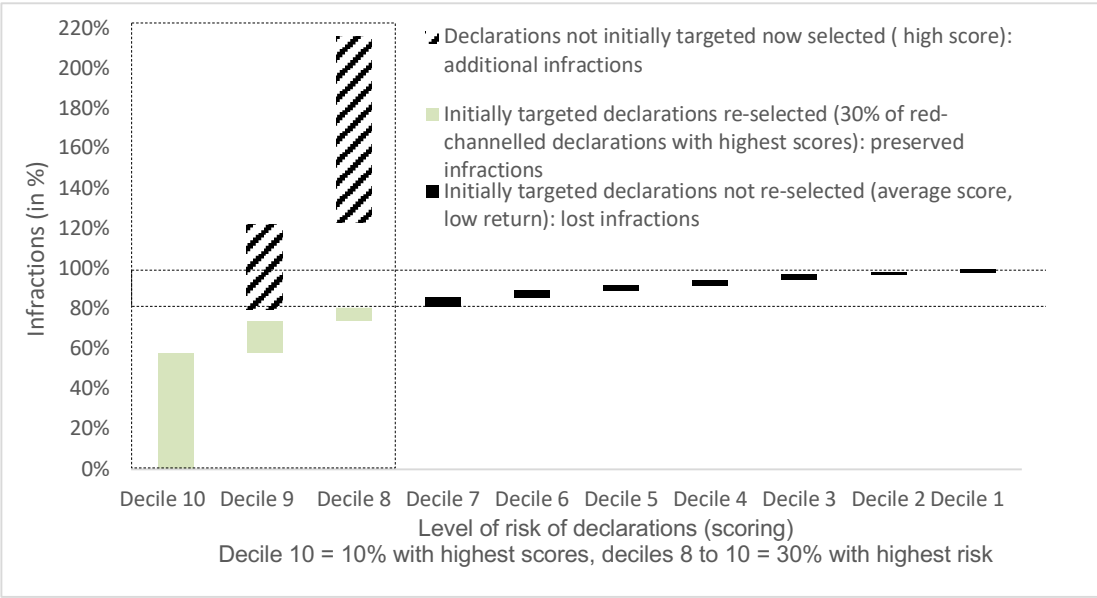
In order to make simulations, the set of declarations have been split in two subsamples. The declarations of the first half of 2016 were used to calibrate the model before computations and simulations are performed over the declarations of the second half of 2016. The simulated selectivity of controls from high scored declarations of the second half of 2016 are henceforth based on the parameters estimated from the first half of 2016, as would be the case in practice. Then, the predictions from the risk-based analysis are matched with the results of the controls that have been actually performed.[4]

The three major outcomes of the simulations presented below are illustrated in the Figure 2 below.

- Result 1: Targeting the declarations to the control channel from a risk-based selectivity would have led to dramatically increase the outcomes of the control while substantially decreasing the rate of physical inspection: only the equivalent of 30 per cent of the previous inspection rate is targeted for physical inspection here.

- Result 2: Focusing on only 30 per cent of the initial rate of inspection through the most high-risk declarations preserves 80 per cent of previously detected offences (green part in the Figure 2 hereafter). This evidences the poor performance of the remaining 70 per cent of the controls resulting in detecting hardly 20 per cent of the offences: reducing the control rate by two thirds ensures that trade is facilitated whilst maintaining the efficiency of control.
- Result 3: scoring allows for simulating the targeting of declarations which hadn't been initially selected for physical inspection. The additional detected offences resulting from these newly selected declarations not only compensate for lost offences (the 20 per cent of the offences that are missed due to the release of the 70 per cent low-risk declarations that had been initially targeted, black part in the hereunder Figure 2), but also substantially increase the rate of detected offences (shaded parts in the Figure 2).

Figure 2: Scoring and selectivity: reduction of the control rate and increase in the offence rate



Source: Author's estimations from anonymised customs data.

Note that the 'type' of the declarations (compliant or not) is only known for the declarations that had actually been sent to a control channel. We henceforth assume for the purpose of the simulations that the probability of detecting offences on high-scored declarations that hadn't been selected for physical inspection would be the same as that of high-scored declarations which had been initially selected for physical inspection. inspection.

The 'gain' in observed offences thus results from the reorientation of declarations that have not been physically controlled but whose score corresponds to the 10th to 8th decile. The 10th decile declarations correspond to the declarations with a score above the threshold allowing a delimitation of the highest 10 per cent, that is, declarations from among the 10 per cent most at risk. The 9th decile features declarations whose score is between the number delimiting the top 10 per cent, and the top 20 per cent highest scores.

The simulation suggests that a substantial reallocation of declarations directed toward the control channel would have enabled a sharp increase in detected offences while strongly decreasing the inspection rate.

The benefits of scoring are twofold. On the one hand, it preserves the same outcome of controls regarding the detected offences rate with much fewer controls: more than 80 per cent (90 per cent) of offences would have been detected with only 30 per cent (50 per cent) of the volume of declarations initially directed towards physical inspection.

Moreover, scoring makes it possible to dramatically increase the number of additional detected offences by reallocating high-scored declarations which hadn't been initially selected as high-risk or targeted by the system. Simulations suggest a potential for increase in detected offences up to 100 per cent. Customs administrations can then both reduce the rate of physical inspection for the purpose of facilitating trade, while increasing the rate of detected offences. Figure 2 illustrates not only the exact compensation (shaded part), which allows the retention of 100 per cent of offences (i.e. the volume of offences remains at its initial level), but also the drastic increase in offences observed of 100 per cent.

5. Conclusion

This article shows how risk analysis helps customs administrations to tackle the dual and seemingly irreconcilable objectives of controlling more to maximise revenue and controlling less to facilitate trade. This article demonstrates that the use of targeting techniques founded on a score that is primarily based on the results of past controls allows for a reconciliation of these two objectives.

The simulation model documented is based on a year of anonymous customs declarations and shows that:

1. The volume of declarations directed toward a control channel can be drastically reduced by impacting only slightly the results in detecting offences: 80 per cent of offences could have been detected by focusing on 30 per cent of the declarations evaluated as being high risk (i.e. with the highest score).
2. The use of such targeting techniques would have made it possible to direct declarations that had not been physically inspected toward a control channel: integrating these declarations in the place of the targeted declarations without convincing results would have made it possible to drastically increase the number of offences observed. Simulations suggest a potential increase in the volume of offences detected up to 100 per cent.

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Notes

1 This method is featured in Asycuda, the automated clearance system developed by UNCTAD.

2 The criteria listed here are not an exhaustive list; the choice of relevant criteria is made in accordance with the data and relevant context.

3 Instead of minimising errors in the linear case.

4 Note that the assessment of the predictive power of the scoring is here very conservative as for clarity purpose we keep the calibration and the simulation periods separated, which implies that the scores at the end of the calibration period are those used for the whole simulation period. Simulations have also been performed from scores which were continuously updated after each new control, i.e even during the simulation period, resulting in a strengthened predictive power.

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Mirror analysis as a support for risk management and valuation: a practical study

Christopher Grigoriou

Abstract

Among the methods of data analysis applicable to and used by customs administrations are mirror analyses, which aim to reconcile a country's import declaration data with exports reported by its partner countries.

This paper illustrates how mirror analyses can be used as a support for risk management, on the frontline as well as in post-clearance audits, and as a support for valuation, highlighting the tariff headings that most frequently experience a reduction in value or those defined as 'safe havens' because of a lower customs tariff.

After providing a methodological reminder, in particular about the importance of the level of disaggregation required for such an analysis as well as the data used and the importance of not being limited to only 'matched' declarations, an application is proposed on the basis of a year of anonymous customs declarations with specific targeting carried out over several chapters of the Harmonized System (HS).

1. Introduction

Mirror analyses, which seek to reconcile a country's import declaration data with exports reported by its partner countries, feature prominently among the data analysis methods used to support customs administrations. This paper demonstrates how mirror analyses can support customs administrations, highlighting the headings that most frequently experience a reduction in value or those defined as 'safe havens' because of their lower Customs tariff.

Section 2 discusses the measurement of discrepancies as a proxy for potential fraud. Section 3 discusses the statistical treatment of data selected for mirror analysis, specifying in particular the importance of orphan import flows and/or mirror exports that should be considered in such analyses. Section 4 emphasises the fundamental importance of levels of disaggregation by focusing on the different possible interpretations of discrepancies observed. Section 5 details the fields of application and highlights how mirror analysis can be useful for frontline and post-clearance controls and provide support for valuation. Section 6 details the results of the study, based on a year of anonymous customs declarations, anonymised for confidentiality reasons, with specific targeting on several chapters of the HS.

2. Mirror analysis: discrepancies as a source of fraud?

2.1 Definition

Mirror analyses are based on comparisons of the same trade flows on the importer's and exporter's sides. Traditionally, cost insurance freight (CIF) and free on board (FOB) ratios are referenced in literature on international trade focused on mirror data. This is because data from COMTRADE, a major source for mirror data[1], is CIF for imports and FOB for exports respectively (see Box 1 below for a discussion of the limits of COMTRADE data). Note that It should possible to directly refer to FOB import values for studies based on customs import declarations data as FOB values are normally recorded in the computerised customs clearance system. In an ideal world, exports reported by partner countries would correspond exactly to import declarations and the presumed ratio between (FOB) imports declared by importers and (FOB) mirror flows reported by exporters would henceforth be 1. This study focuses on data pertaining to import declarations, but we still had to consider CIF imports as FOB data were not available for the period of research. In an ideal world, the ratio between imports and exports would then be here about 1.06, to take into account the typical spread between CIF and FOB values (see Hummels & Lugovsky, 2006).

2.2 Interpretation of discrepancies as a source of fraud

A major challenge of mirror analysis lies in the precise identification of the origin of the observed deviations. These differences can indeed prove legitimate and be attributed to various logistical causes. Problems with customs procedures can also be at the root of such discrepancies. It is therefore essential to understand the reasons underlying the differences observed. Analysis of investigation services should make it possible to distinguish gaps that can be explained by potential irregularities from gaps attributable to logistical issues (see Cantens, 2015, for a guide on the use of mirror data).

The 'M–X' gap may not, in fact, be related to fraud. Import data are typically recorded with greater care than export data as tariffs are usually calculated on imports and not on exports. Transit or re-export situations may also create discrepancies, particularly if in the case of a re-exported commodity, the importers declare the country of origin while the exporter declares the last *known* destination of the goods, in accordance with the recommendations of the United Nations. Similarly, the minimum thresholds at which economic operators are forced to report their trade flows may differ from one country to another, also leading to sources of deviations that are not associated with deliberate fraud.

The 'M–X' gap may reveal deliberate fraud. The undervaluation of goods to reduce the amount of duties and taxes to be paid is a reason conventionally offered to explain a negative difference ($M < X$). Several econometric studies have empirically demonstrated a positive correlation between mirror deviations and the magnitude of the customs tariff (e.g. Fisman & Wei, 2004; Carrère & Grigoriou, 2015). There are also tariff shifts leading to the declaration of goods with a high rate of taxation under a different tariff heading in order to unduly benefit from a lower tariff. This results in a negative deviation for goods with high tax rates. Finally, there is also the case of smuggling and non-declarations whereby tariff descriptions are not declared on the import side, although they have been recorded on the export side. The overvaluation of imports may, on the contrary, be observed in the context of transfer pricing mechanisms or when an economic operator seeks to drive capital out of the country. The mechanism underlying the aforementioned tariff shifts could also lead to positive deviations for headings that will serve as 'safe havens' on account of their low tax rates.

Box 1: Use and limitations of COMTRADE data

Mirror data, or exports reported by partner countries, are sourced primarily from COMTRADE. This database is managed by UNCTAD, a United Nations body that centralises, harmonises and makes international customs trade flows publically available, provided that the customs administrations submit their data. This database can be accessed via the United Nations Statistics Office. The exports data refer to FOB values expressed in US dollars and weights. The data refer to subsections, i.e. HS6 product groupings, the maximum level of disaggregation for which there is a harmonised code at the global level.

Limits of COMTRADE data

The use of COMTRADE data has two limits: 1) the data compilation time and 2) the fact that certain data are not shared.

The collection and harmonisation of global customs data takes time. It takes at least one year to compile complete data from the year before, an absolute prerequisite for interpreting the gaps observed as potential sources of irregularities. This is not a problem if the goal is to provide information for post-clearance audit services that typically have up to three years after the declaration is filed to intervene. However, although the process of compiling one year's worth of data is long, it is possible to procure partial data more rapidly. UNCTAD's statistical department process and publish the data online if they receive them from the different customs administrations. They can then be used for comparative purposes, for example comparing the value and weight of certain headings. Some countries do not transmit their data to UNCTAD and, as a result, they do not appear in the mirror flows. This is the case, for example, with Afghanistan, Cuba and Gabon. Import declarations from the customs declaration databases of these countries are therefore not considered, as otherwise an artificial gap would be created. This would indeed involve reconciling headings with import declarations that contain no 'match' in the mirror data; simply because of an absence of information and not for any issue of tariff shifting, or under-declaration of value or origin etc. as it could be erroneously suspected. The volume of imports corresponding to exporting countries not transmitting their data to UNCTAD represents about 10 per cent of (non-petroleum) consumption for 2016. These data are removed from the imports that are examined within the mirror analysis framework.

3. Reconciliation of the data: going beyond 'matched' flows

Comparisons of import data with corresponding mirror flows reported by exporting countries reveals three potential situations, outlined below.

- Flows are said to be 'matched' when the correct tariff description is reported by both the importing and the exporting countries, the same flow being appropriately reported by the two partners.
- 'Orphan imports' occur when the trade flow is listed on the importing customs declaration, but is missing on the side of the partner country, thereby indicating either a tariff shift or origin fraud.
- 'Lost exports' refers to trade flows reported as exports by partner countries without any corresponding declaration being recorded in the import declarations data of the customs administration concerned, indicating potential smuggling or imports without declarations.

The analysis should not be limited to 'matched' trade flows as the subsequent mirror analysis would be biased, severely minimising the magnitude of the misdeclarations. Mirror analyses are however often limited to 'matched' trade flows as they are focused on the M_{ij}/X_{ji} ratios, which cannot be computed where mirror data are missing. This provides a partial view of reality as 'orphan import' or 'lost exports', which are serious indicators of tariff shifts, are then excluded from the analysis. The elimination of 'orphan import' and 'lost exports' for the analysis represents indeed a loss of a substantial amount of

information given the multiplication of such flows as the level of disaggregation increases (see Carrère & Grigoriou (2015) for an overview of the concepts of orphan imports and mirror exports, as well as a specific model for orphan imports).

4. The importance of disaggregated data (HS6)

The greatest level of disaggregation possible should be used for the purposes of analysis. If the analyses can be initiated at the chapter level, that is a big contributor to revenue, or represents a large volume of declarations or seems to contain irregularities (significant differences in $M_{ij} – X_{ji}$), it is essential to go down to the finest level of disaggregation (HS6), as similar gaps at the chapter level can conceal very different situations.

The deviation calculated at the chapter level (M–X) can conceal different situations at the section (HS4) and subsection (HS6) level (see Table 1 below). A neutral deviation ($M_{ij} = X_{ji}$) at the chapter level can reveal diametrically opposed cases. This neutral gap may correspond to a 'healthy' chapter, the volume of exports reported by the partner countries corresponding exactly to the imports declared by the importers. But this neutral gap can also conceal cases of under/over declarations of value or quantity (weight) or significant tariff slips in opposite directions from one section or subsection to the other which are balanced out when the sections/subsections are aggregated.

A neutral deviation at the chapter level may thus correspond to a situation whereby revenues are strongly impacted by fraud if the deviation conceals tariff heading shifts of the sections with the highest tax rates toward the lower tax rates. Chapters with deviations (M–X) that are positive (M > X) or negative (M < X) can also hide opposing situations, with sections or subsections with higher tax rates more likely to be affected by problems of under-declarations of value or tariff shifts. Not all chapter headings will be the subject of a possible investigation.

A large discrepancy should not systematically be equated with under/over declarations of value but can result from a tariff shift from one chapter to another or from a fraud on the origin. A negative deviation (M < X) of a chapter may for instance result from the aggregation of a 'healthy' section or subsection with another section which contains lost exports. Conversely, the positive deviation (M > X) of a chapter or section can result from the compilation of data of a 'health' section or sub-section with another section which contains orphan imports.

Table 1: Potential interpretations of gaps $M_{ij} – X_{ji}$ at the chapter level

Observed situation for a particular chapter	Potential explanation	Illustration in the case of a chapter with two sections
No significant gap ($M_{ij} = X_{ji}$)	'Healthy' chapter, no irregularity, declared imports actually correspond to what is reported by the trading partners	Exports to country A from country B exactly match imports declared by country A from country B for all the goods of the two sections of the considered chapter
	Agregation at the chapter (or section) level conceals gaps that would have been observed at a more disagregated level	Tarif shifting or fraud on the origin of opposite sign for the two sections of the chapter $M_{ij} < X_{ji}$ for goods with a high taxation rate (or at the limit: lost exports), e.g. the first section of the chapter $M_{ij} > X_{ji}$ for goods with low taxation rate (or at the limit: orphan imports), e.g. the 2nd section of the chapter. This mechanism can obviously also occure when aggregating from subsection to section.
$M_{ij} – X_{ji} <0$	Underdeclaration of at least a part of the chapter. It can result from underdeclaration of the values or quantities, or fraud on the origin or tarif shifting, (e.g for high tariff headings). The gap at the chapter level can also result from the aggregation of goods with lost exports with 'matched' goods.	1st case: the two sections have goods with substantial underdeclaration of values or quantities, leading to a global gap ($M_{ij} < X_{ji}$). 2nd case: the gap $M_{ij} – X_{ji} <0$ at the chapter level results from the agregation of the gaps of two sections with one of them having lost exports. As no import is reported by the trading partners for this section (M = 0), imports henceforth concern values for only one section while exports are reported for the two sections.
$M_{ij} – X_{ji} >0$	Overvaluation of at least a part of the chapter. Fraudulent situation related to transfer pricing or capital flights, notably for intra-group trade flows. This situation may correspond to tariff shifts 'at the benefit' of a lower-tarif chapter, or to a fraud on the origin to unduely take advantage of more favourable conditions in case of regional trade agreement. The gap at the chapter level can also result from the aggregation of goods with orphan imports with 'matched' goods.	1st case: the two sections have goods with substantial overvaluations or overdeclarations of quantities leading to a positive gap in each of the section of the chapter ($M_{ij} > X_{ji}$) and subsequently to a positive gap at the chapter level. 2nd case: the gap $M_{ij} – X_{ji} >0$ at the chapter level results from the agregation of the gaps of two sections with one of them having orphan imports: no exports is reported on the exporting side for this section (X = 0). Exports data henceforth concern the values of a single sections while imports data consider the values of two sections.

Note: interpretations can be processed similarly on the weights gap.

The positive deviation at the chapter or section level may result from the aggregation of a healthy section or subsection with one containing orphan imports. The same rationale governing the case of lost exports can induce a negative gap ($M_{ij} < X_{ji}$) when moving to a higher level of aggregation.

These mechanisms are true for any aggregation–disaggregation step, whether from chapter (HS2) to section (HS4) or from section to subsection (HS6).

5. Mirror analysis, from selective controls to a support for valuation

Mirror analyses as a support to customs administrations are in principle more suited to post-clearance audits because discrepancies cannot automatically be presumed to be offences. Results must therefore be examined by investigative services. Furthermore, the delays often inherent to the collection of mirror data imply a significant time lag between results obtained and future declarations, making the data more appropriate for a post-clearance audit than for frontline control services.

However, the immediacy of the operational implementation of these analyses can, in certain conditions, render mirror analysis quite effective for first line control also (see Raballand et al., 2013). These analyses do not have any particular IT requirements other than the automated clearance system, which is already present in almost all customs administrations, nor additional data requirements, such as feedback from physical controls. The use of mirror analyses can thus allow for the establishment of risk management for frontline control and ensure that declarations targeted for physical inspection are identified in an objective manner. It can also be used to provide more information on a target identified on the basis of scores formulated using the results of past controls.

Finally, mirror analysis provides significant support for valuation as it highlights headings experiencing the most value reduction and others acting as safe havens on account of the application of lower tariffs. This aspect of mirror analysis is all the more relevant in the context of the re-appropriation of customs-related powers by a number of customs administrations that had for many years outsourced these tasks to private companies under the Import Verification Program (IVP).

6. Mirror analysis as a support to customs administrations: application

This section illustrates the mirror analysis methodology from a study case relying on a year of customs declarations, anonymised for confidentiality reasons.

6.1 The global level

At the most aggregated level, that is, by comparing the sum of imports with the sum of exports (whether there is a match or not), we obtain the ratio of 0.74 from the ratio of values, and 1.01 from the ratio of weights, implying a missing sum of 25 to 30 per cent on the import side (see Table 2 below), if transport costs are taken as 6 per cent of the FOB value. This ratio denotes a major issue with regard to under-declaration of value, which is not found on the quantity side (ratio comes close to 1, as expected). This ratio, which is already considerably weak, conceals even wider gaps that would suggest the presence of value, tariff heading or origin fraud.

Table 2: Overall trade, exports and imports (2016)

Aggregated level	Value (rounded up to 100 for exports)	Weight (rounded up to 100 for exports)
Total imports (CIF)	74	101
Total exports (FOB)	100	100
Ratio	0.74	1.01

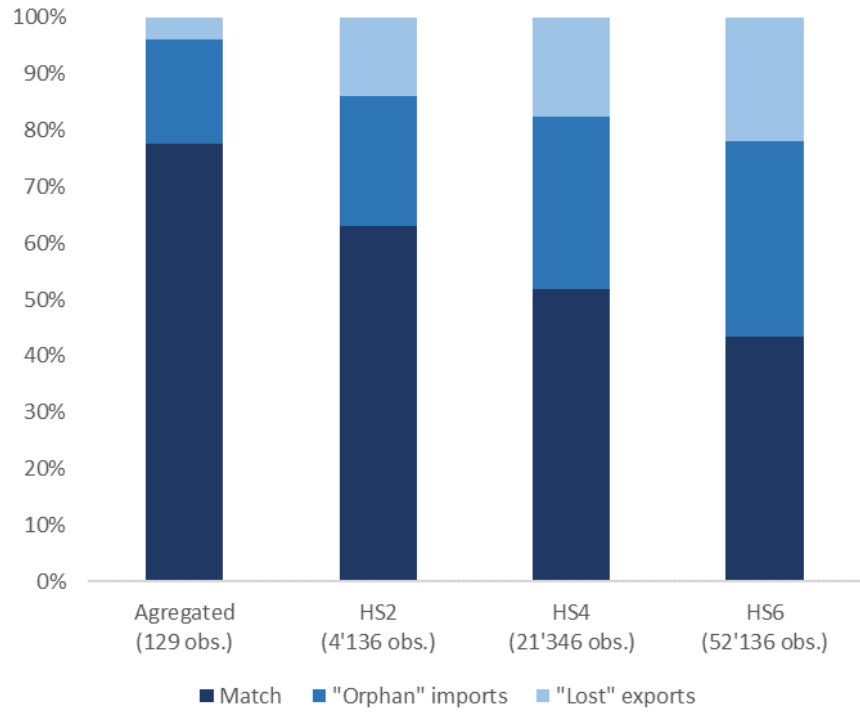
Source: Author's calculations on the basis of anonymised Customs and COMTRADE data.

Data normalised for an export total of 100 to maintain data anonymity.

The disaggregated analysis hints at significant gaps potentially linked to falsified value, tariff headings or origin in declarations.

Chart 2 below illustrates the splitting of trade flows between corresponding flows, orphan imports and lost exports according to the level of disaggregation (HS2, HS4, HS6). A flow corresponds to 'one line' (i.e. there are as many lines as there are partner countries at the aggregated level), and as many lines as partner countries, chapters at the HS2 level, etc.

Figure 1: Mirror analyses by partner country, different levels of aggregation, 2016



Source: author's calculations from anonymised Customs and COMTRADE data.

The bulk of trade flows are mirrored at the aggregated level. Eighty per cent of the lines represent matching flows (dark blue portion in Figure 1) while 15 per cent of the lines represent orphan imports and 5 per cent lost exports. But this global harmony at the aggregated level conceals large gaps, whether tariff shifts or origin fraud. Both partners report only 43 per cent of the lines when the most disaggregated level of mirror data (i.e. HS6), is considered. The remaining 57 per cent are either orphan imports (35) or lost exports (22%).

6.2 Selection of chapters to study and identification of specific tariff headings to investigate

The decision regarding which HS chapters should be examined can be made according to various criteria. First, it is important to observe the deviations associated with chapters as an indicator of potential irregularity. These can either be very positive (M > X) or very negative (M < X), with each case being associated with a separate potential fraud pattern. It should be noted that weight differences will be used primarily for bulk goods or where the value attributed to the goods is weight dependent. The magnitude of the gap, as a rule for analysing the chapter, can be combined with other elements contained within the chapter. For example, how significant a chapter is in terms of overall revenue or the overall volume of imports may warrant further investigation. The effective tax rate of the chapter can also be taken into account because of the fraud schemes that may be associated with it: a positive difference is expected when the effective rate is low and vice versa.

Once the chapter to be analysed is selected, the M–X deviations, the value of the orphan imports and the associated lost exports are observed. The next level of disaggregation, that is, the sections (HS4) are then identified. The aim is to identify those sections that are likely to make up the overall gap, focusing attention on both M–X differences by section and on orphan imports or lost exports. The analysis is then repeated at the next disaggregation level (subsection, HS6). This approach ensures that the gaps are disassembled within the chapter and accounts for possible shifts from one section or subsection to another that could be compensated for when moving to the higher level of aggregation.

6.3 Case study: application of the study to four identified chapters

The following tables illustrate this approach with an analysis of four chapters—85, 30, 29 and 25—relating to electrical appliances, pharmaceuticals, chemicals and mining products.

Case study 1: Electrical appliances (Chapter 85)

Chapter 85 deals with electrical appliances. It was selected because initial analysis revealed that it was one of the chapters with the strongest—'more negative'—M–X gap, with an effective tax rate of around 18 per cent, and accounted for a high percentage of imports, between 5 per cent and 10 per cent of the total import volume (excluding petroleum products). Table 3 hereunder reports the decomposed gap, withing the most striking sections and subsections of the chapter. Orphan imports and lost exports of the corresponding headings are also reported.

Table 3: Electrical appliances (Chapter 85)

Tariff heading			Gap M–X (in millions of USD)	Orphan imports (in millions of USD)	Lost exports (in millions of USD)	Effective tax rate
HS2	**HS4**	**HS6**				
85			**–1780.0**	**3.200**	**0.140**	**18.73%**
	8533		**–70.0**	**0.061**	**0.010**	**13.51%**
		853332	–65.0	0.010	1.500	14.37%
	8536		**–440.0**	**0.790**	**0.013**	**21.20%**
		853610	–44.8	0.072	0.970	19.05%
		853650	–40.2	0.360	0.002	23.85%
		853669	–79.4	0.061	0.033	23.51%
		853690	–245.0	0.203	0.010	19.38%
	8538		**–153.0**	**0.210**	**0.014**	**15.90%**
		853890	–152.0	0.206	0.014	16.48%
	8542		**–307.0**	**0.760**	**0.160**	**13.90%**
		854231	–59.5	0.660	**12.600**	13.11%
		854239	–42.6	0.070	0.001	16.31%
		854290	–181.0	0.002	0.035	7.32%
	8544		**–352.0**	**0.440**	**0.050**	**16.88%**
		854411	–18.2	0.016	0.014	17.86%
		854419	–12.0	0.017	0.300	16.64%
		854420	–10.0	0.010	3.300	0.25%
		854430	–134.0	0.170	0.060	0.22%
		854442	–78.3	0.113	0.001	24.30%
		854449	–75.6	0.500	1.030	11.10%
		854470	–15.5	0.019	0.170	16.23%
	8547		**–90.1**	**0.042**	**6.100**	**0.40%**
		854720	–87.0	0.0015	1.330	18.40%

Source: author's calculations from anonymised Customs and COMTRADE data.

The analysis shows that there are very few cases of orphan imports or lost exports for this chapter and it can therefore be induced that the differences result mainly from undervaluation. It also appears that the value differences between import declarations and their mirror data increase along with the effective tax rate.

Case study 2: Pharmaceutical products (Chapter 30)

Chapter 30 deals with drugs (pharmaceutical products). This is of course a very sensitive chapter as it revolves around public health issues, particularly as fraud involving medications has been steadily increasing in recent years. This case makes it possible to highlight how more aggregated levels can hide deviations in the opposite direction. Finally, this case also illustrates how aggregation can inflate the differences at the most aggregated level by integrating orphan imports with 'matched' flows.

Table 4: Pharmaceutical products (Chapter 30)

Tariff heading			Gap M–X (in thousand of tons)	Gap M-X (in millions of USD)	Orphan imports (in millions of USD)	Lost exports (in millions of USD)	Effective tax rates
HS2	**HS4**	**HS6**					
30			–1.000	–14.3	1.70	0.30	0.32%
	3002		0.000	–52.8	1.30	0.20	0.40%
		300210	–29.000	–55.7	1.00	0.10	0.00%
		300220	0.030	4.7	1.20	2.00	0.00%
		300230	0.002	–2.2	3.40	0.10	0.00%
	3003		1.800	110.0	26.20	0.10	0.00%
		300390	1.500	**108.0**	**31.70**	0.00	0.00%
	3004		–3.100	–93.4	1.10	2.10	0.01%
		300410	–	–	–	2.00	
		300420	–0.140	–8.4	0.60	5.20	0.01%
		300431	0.000	–2.3	8.80	1.20	0.00%
		300432	–0.050	–2.1	–	4.40	0.00%
		300439	–0.040	–7.9	0.30	6.60	0.01%
		300440	–0.003	–1.1	0.00	6.90	0.09%
		300450	–0.060	–2.9	0.50	0.50	0.01%
		300490	–2.400	–54.3	2.00	0.80	0.01%
	3006		–0.050	–3.8	0.36	0.13	5%

Source: author's calculations from anonymised Customs and COMTRADE data.

The analysis of the above data from Chapter 30 is indicative of the potential use of safe havens, as is often the case for fraud committed on this type of subheading (cosmetics etc.). If the M–X deviation at the chapter level (HS2) is moderate, either in value or in weight, significant differences in opposite directions occur at the section (HS4) or subsection level (HS6), for example section 3002 and 3004 versus section 3003 (wholesale versus packaged products). Such evidence reinforces the aforementioned argument for exploiting data at the most disaggregated level; it is clear that aggregated data can mask significant discrepancies. The exploitation of 'unrequited' data, whether for orphan imports or lost exports, is essential since it reinforces the idea of a tariff shift from one section to another. Consequently, there is a high level of orphan imports associated with Section 3003 (i.e. declarations of imported products from Section 3003 without a reported flow of corresponding exports by partner countries), accompanied by a significant amount of lost exports for Section 3004 (export flows reported by partner countries that are not found in the country's import declarations). Furthermore, the differences in weights, small in magnitude, are not consistent with the differences in values, which reinforces the idea of a shifting tariff.

Case study 3 – Chemical products (Chapter 29)

Chapter 29 deals with chemical products. This chapter is targeted among the chapters to be analysed due to its significant, and positive, M–X spread, whether with respect to over-declarations of values or the predominance of safe havens used to deliberately misclassify items on account of the lower-than-average effective tax rate of 11 per cent, which is significantly lower than the average rate for all imported items.

This chapter again illustrates the importance of focusing efforts on higher levels of disaggregation and across trade flows; not just on data matching according to the import and export mirror flows, but also on data that lack a corresponding mirror flow. The analysis shows that about half of the deviation observed at the aggregate level comes from orphan imports. The bulk of the orphan imports observed at the highest level of disaggregation (HS6) are associated with subsection 294110 with an effective tax rate of 6.30 per cent, a rate so low that it seems to validate the use of this heading as a safe haven.

Table 5: Case study 3: Chemical products (Chapter 29)

Tariff heading			Gap M–X (in millions of USD)	Orphan imports (in millions of USD)	Lost exports (in millions of USD)	Effective tax rate
HS2	**HS4**	**HS6**				
29			89.1	1.5	0.4	11.00%
	2905		**4.4**	**0.3**	**0.1**	**15.00%**
	2915		–	**12.7**	**–**	**17.60%**
		291531	–	2.5	–	18.50%
		291532	–	4.4	–	18.50%
		291533		1.3		18.50%
		291560		1.1		18.50%
		291590		1.3		18.50%
	2916		**1.9**	**0.4**	**0.0**	**18.50%**
	2917		**0.6**	**5.9**	**–**	**13.80%**
		291735		2.1		18.50%
		291739		2.5		6.40%
	2930		**8.0**	**0.0**	**0.0**	**12.50%**
		293040	0.2	5.0	0.1	8.24%
		293090	2.9	0.1	0.0	16.70%
	2933		**9.1**	**1.7**	**0.0**	**16.68%**
		293329	3.9	0.1	0.0	6.30%
		293339	2.2	0.0	0.1	6.90%
		293399	0.9	2.6	0.0	6.70%
	2941		**13.0**	**18.7**	**0.1**	**6.30%**
		294110	–	22.0	–	6.20%
		294150	–	3.4	–	6.30%
		291490	3.0	2.1	0.1	6.60%
	2942	294200	–0.9	–	1.7	6.00%

Source: author's calculations from anonymised Customs and COMTRADE data.

Case study 4: Mining products (Chapter 25)

Chapter 25 deals with mining products (salt, stones, and cement, which is a major import, particularly for many developing economies). This chapter is targeted as it is that with the highest level of under-reporting.

Table 6: Mining products (Chapter 25)

Tariff heading			Gap M–X (in thousand of tons)	Gap M-X (in millions of USD)	Orphan imports (in millions of USD)	Lost exports (in millions of USD)	Effective tax rate
HS2	**HS4**	**HS6**					
25			**–586.0**	**–31.0**	**1.1**	**9.1**	**20.60%**
	2503	**250300**	**–495.0**	**–28.0**	**3.1**	**6.7**	**18.50%**
	2511	**251110**	**–35.1**	**–2.9**	**0.3**	**–**	**13.20%**
	2515		**–2.5**	**–1.1**	**0.0**	**–**	**30.80%**
		251511	–68	–6.4	–	0.0	30.70%
		251512	6.03	5.1	0.3	–	30.80%
	2517		**–35.7**	**1.2**	**0.0**	**0.0**	**19.50%**
		251741	–39.9	0.8	0.0	0.0	19.80%
	2529		**–32.0**	**–4.0**	**0.2**	**3.2**	**18.50%**

Source: author's calculations from anonymised Customs and COMTRADE data.

The analysis in this chapter shows that the weight gap observed at the chapter level as a whole is largely based on a subsection (250300), the content of which should be further explored. There is also a probable tariff shift between subsections 251511 and 251512, however, this may not be due to deliberate tax evasion as the two positions have similar effective tax rates.

7. Conclusion

This chapter illustrates how mirror analyses can be used as a support for risk management, to some extent for frontline controls but even more for post-clearance audit, and as a support for valuation, highlighting the headings that most frequently experience a reduction in value or those used as 'safe havens' because of a lower customs tariff.

Mirror analyses are *a priori* more suitable for post-clearance audits, as their insights must be investigated by intelligence services before it triggers a control and as there is a time lag between the clearance of declarations and the collection of mirror data. However, the immediate operational implementation of mirror data analyses could prove to be effective for first-line controls for customs administration with no database on the previous controles of the frontline controls. Such analyses indeed do not have any particular IT requirements other than the automated clearance system, which is already present in almost all customs administrations, nor additional data requirements, such as feedback from physical controls. The use of mirror analyses can thus allow to initiate risk-based targeting for frontline control and ensure

that declarations targeted for physical inspection are identified in an objective manner. Finally, mirror analysis serves as a good support to valuation, or headings defined as safe havens because they attract lower customs tariffs.

This aspect of mirror analysis is particularly relevant in the context of the re-appropriation of customs-related powers by a number of customs administrations that had for many years outsourced these tasks to private companies under the Import Verification Program (IVP).

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Notes

1 Bilateral data can, beyond COMTRADE, be sourced on a case-by-case basis from countries whose statistical services make their bilateral foreign trade data publicly available. This is the case, for example, of the United States or the European Union. These databases contain up-to-date informaton that may be more recent that those from COMTRADE but they are by definition less exhaustive than COMTRADE.

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How helpful are mirror statistics for Customs reform? Lessons from a decade of operational use

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Abstract

From a tool for trade economists, mirror data, which consist of comparing export and import data reporting by exporting and importing countries, have been increasingly used to detect potential fraud in developing countries. This dramatic change can be explained by the simplicity and low cost of using open worldwide databases. Even though mirror data discrepancies do not guarantee fraud records, this approach contributes to improved risk analysis (on origins and tariff lines, as well as brokers/importers, locations and inspectors), estimates of potential revenue losses, and new dialogue between customs administrations, importers, brokers and, sometimes, political authorities. The use of mirror statistics in developing countries is, therefore, promising and should be used increasingly for customs reforms. However, this statistical tool is even more efficient with other reforms, such as human resources reforms.

1. Introduction

Over the last decade, customs administrations have increasingly been using mirror statistics. This involves comparing export and import data reporting by exporting and importing countries.[1] While such analysis began in the mid-1960s, its use was limited to solving statistical issues in the field of trade economists for more than forty years. The dramatic expansion of its use can be attributed to mirror analysis contributing to the literature on governance and the discovery that it is an excellent operational tool for customs administration all over the world.

This paper demonstrates how mirror statistics can be helpful and operationalised almost immediately by customs administrations, especially in developing countries, to help improve risk analysis and fraud detection. It shows how powerful it can be and how it has been used by customs administrations in the last decade.

The use of mirror statistics began with trade economists in the 1960s. They have increasingly used mirror data to overcome the issue of missing values and insufficient quality in the reported data, increasing both the size and the quality of their samples. Mirror data were used for statistical purposes, for example exports from country j to country i would henceforth be used as substitutes for the reported data of imports of country i from country j, either because the data reported by trading partners are considered as more reliable or to deal with countries that do not report their data at all.[2] This was pioneered by Bhagwati (1964). Import data[3] reported by country i from country j are usually considered as more reliable than the symmetrical exporting flow from country j to county i. Indeed, customs clearance processes, mostly occurring on the importing side, constrain the importers to a detailed declaration of the goods, including details such as their value, classification and weight.

After being used to increase database observations, mirror data have been used by trade economists as a common way to proxy trade costs, particularly transportation costs. Imports are traditionally reported CIF (cost insurance freight) while exports are registered FOB (free on board). Then, in a perfect world, the discrepancy between the two registered trade flows of the same good *k* (M_{ijk}/X_{jik}) should be trade costs. The ratio (M_{ij}/X_{ji}) is often reported as the CIF/FOB ratio in the literature. Yeats (1978), Rose (1991), Baier and Bergstrand (2001) and Hummels and Lugovskyy (2006) illustrate this frequent use of the mirror data.

However, while the use of the ratio (M_{ij}/X_{ji}) to proxy the trade costs makes common sense, empirical analysis from these authors evidenced that if a part of the (M_{ij}/X_{ji}) ratio was mechanically measuring trade costs (CIF vs FOB), the ratio clearly captures 'something else', as in many cases observed gaps appeared to be erratically driven. While one would expect a ratio in a range of values between 1.06 to 1.20, reflecting trade costs between 6 per cent and 20 per cent of the goods value[4], ratio could be in a high number of cases either smaller than 1, suggesting negative trade costs (!), or conversely, higher than 2 or 3, suggesting trade costs way high to be credible. Hummels and Lugovskyy (2006) exhibit from a sample of 17,790 country pairs of 1997 that hardly 50 per cent of the total bilateral trade flows have magnitude orders that could be considered as 'reasonable', while ratios computed from their sample often happened to be lower than 1.

This highlighted the fact that 'something else' other than just the transportation costs were captured by this ratio.[5] Some authors argue it was pure noise, suggesting that country pairs exhibiting 'abnormal' ratios be removed from empirical analysis. However, more disaggregated data has shown that such 'abnormal' ratios are usually focused on some country origins and for a limited number of products or tariff lines and most tariff lines and origins do not exhibit such problems.[6]

New literature in the last two decades has demonstrated the importance of poor governance on mirror statistics discrepancies, enabling its use to go beyond this 'something else' and to dramatically expand the field of use of such data.

The remaining sections present the wide variety of mirror statistics used to capture governance problems, demonstrate the most operationally relevant use for customs administrations and shows some possible way forward on how to make the use of mirror statistics even more efficient.

2. Mirror data – a reliable instrument to capture governance problems

Customs fraud may be in the form of under/overvaluation, misclassification, smuggling or fraud at origin. These are the main avenues through which unscrupulous traders undertake international trade-based money laundering and illicit financial flows (IFFs). Spanjers and Salomon (2017) estimate that 87 per cent of the IFFs in the developing countries from 2005 to 2014 were through trade mis-invoicing. This is why it is critical for Customs to detect potential under/over valuation and misclassification to prevent tax evasion, money laundering and IFFs. A large body of literature has demonstrated empirically the correlation between the mirror statistic discrepancies (for a limited number of products) and corruption or taxation, both at the global level and the country level.

Poor governance at land borders or ports, reflecting both a lack of capacity or skills and/or corrupted customs officers in collusion with fraudulent importers, may result in undervaluation or misclassification in customs declarations. Substantial undervaluation in imported goods by fraudulent importers willing to evade taxes will result in lowered M_{ij}/X_{ji} ratio. Mirror data are henceforth used here to compute the M_{ij}/X_{ji} ratio in order to capture poor governance issues at the border, trying to identify any pattern

and relationship between the ratio and governance or macroeconomics variables through econometric models. Misreporting can be on the values, on the quantities or on the goods classification to evade taxes by declaring a tariff line from a lower tax band.

Recent papers mostly consider 'abnormal' ratios (e.g. too high (over 50%) or smaller than 1), reflecting governance issues related to customs clearance. Empirically, worldwide or country analysis points again and again to poor governance, such as the level of corruption or tariff evasion to escape the high level of taxation faced by certain goods.

2.1 At the global level

Part of the literature has over the last decade focused its attention on the correlation between mirror statistics discrepancies and macroeconomic variables regarding governance and public sector integrity indicators, such as corruption level, tariff level and the complexity of its structure.

Carrere and Grigoriou (2014) use a gravity equation over a worldwide panel at the HS6 level (3.5 million observations) to highlight a robust relationship between the M_{ij}/X_{ji} ratio and macroeconomic variables like the average tariffs, but also foreign direct investment, suggesting profit shifting, and the implementation of regional trade agreements. They furthermore run a probit estimate over 7 million observations to predict 'orphan imports', which are imports reported by importing countries without the equivalent flow reported by the exporting country. Up to 68 per cent of the misclassification cases are accurately predicted by the set of macroeconomic variables previously mentioned. Carrere and Grigoriou conclude that discrepancies from the mirror data are not erratically driven, part of the ratio being predicted by macroeconomic variables, suggesting a relationship between misreported trade flows and fraud opportunities to evade tariffs and taxes and/or poor governance.

Javorcik (2017) uses the M_{ij}/X_{ji} ratio to test the impact of World Trade Organization (WTO) accession on tariff evasion. Indeed, countries accessing WTO are committing to World Customs Organization (WCO) valuation agreements, implying an increased level of transparency from customs officials, (expectedly) resulting in lowered corruption and undervaluation (increased ratio M_{ij}/X_{ji}). From the sample of 15 countries having joined the WTO between 1996 and 2008, they find that tariff evasion through underreported values decreased after the accession, even though it is substituted by underreporting of the quantities where the tariff rate has been increased after the accession.

2.2 At the country level

Fisman (2004) demonstrates that, in the context of the bilateral trade between China and Hong Kong, there is a significant relationship between the 'evasion gap' and the tax rates: the higher the tariff and tax rates, the lower the Mij/Xji gap (i.e. the higher the undervaluation of imports). Fisman's findings suggest that this tax evasion is processed not only through undervaluation but also through misclassification.

Javorcik (2008) demonstrated similar findings over German bilateral trade, highlighting a strong correlation between the discrepancy and the tariff level, which appeared to be even stronger for differentiated products. Javorcik concludes that, in the German context, the discrepancies largely reflect poor reporting.

Rijkers (2015), looking at Tunisian bilateral trade, showed that the correlation between the discrepancy and the tariffs is not homogeneously distributed but is strongly correlated to the proximity of the importer with the political power (i.e. the discrepancy is stronger when the importer is close to the government). In the same country, Tunisia, Ayadi, Benjamin, Bensassi and Raballand (2013) assessed that at the disaggregated level of trade data, for common reported flows between Tunisia and Libya and Algeria, underreporting of imports by Tunisia Customs was, on average, around a factor of 3. The potential large undervaluation by two-thirds of the export price value was confirmed by surveys at borders and it was estimated that informal trade with Algeria was higher than the official trade.

Many other applications of the use of mirror statistics have been performed over almost all regions of the world to detect statistic discrepancies and map sectors and goods with the highest observed discrepancies, which can only be explained by fraud practices or smuggling. To name some, Kaminski and Raballand (2009) could be quoted on Central Asia; Raballand and Mjekiqi (2010) on Nigeria; Bensassi, Brockmeyer, Pellerin and Raballand (2015) on Mali; and Hamanaka (2011) on Cambodia.

Finally, Anson, Cadot and Olarreaga (2006) use the M_{ij}/X_{ji} ratio to assess improvements in governance at the border in the context of pre-shipment inspection program (PSI), considering most of the poor governance is explained by undervaluation by importers, in collusion or not with customs officers. They henceforth regress the M_{ij}/X_{ji} ratio on a set of explanatory variables, including a variable to capture the potential impact of PSIs, trying to measure their ability to decrease the fraud and, consequently, increase the collected taxes at the border. Empirical analysis relying on bilateral trade data for Philippines, Indonesia and Argentina reveal mixed evidence of the impact of PSIs on undervaluation.

3. Mirror data to identify fraud channels and the operational use for customs administrations

Another wave of studies identifies fraud channels and quantify possible revenue losses at a macroeconomic level. It started with a detailed analysis done in Cameroon (Raballand, Cantens, & Guillermo; 2012), then in Tunisia (Ayadi et al., 2013), in Mali (Bensassi et al., 2015) and in Madagascar (Chalendard et al., 2016). In the meantime, WCO published a research paper to explain how to use this method operationally for customs administrations (Cantens, 2015). Other similar studies were carried out in some Sub-Saharan African (SSA) countries even though not published.

All these studies have in common that they were carried out at a disaggregated level (HS6[7]), in countries facing smuggling and widespread fraud practices, high levels of corruption and relatively complex tariff structures (although slightly less relevant for Madagascar).

These studies, while carried out in different sub-regions, have interestingly led to some invariant findings:

1. A strong correlation between tariff peaks (and tariff complexity) and statistics gaps.
2. Gaps are limited to less than 10 products BUT in all countries, statistics gaps are for the same types of products (which are usually considered at risk by customs administrations).
3. The main gaps concern some food products (vegetable oil, sugar, rice), clothes and footwear, some manufactured products (motorcycles, phones), construction materials (including cement), fuel, low-selling price density (such as fertilizers) or products exempted from duties/VAT in some countries (like rice).
4. In terms of estimates of revenue losses, even though they are minimal estimates, at least 20 per cent to 30 per cent of total customs revenues can be identified through mirror statistics largest discrepancies.

The increasing operational use of mirror statistics by customs administrations can be explained by the following reasons:

- it is easy to use to initiate or rapidly improve risk analysis
- it generates numbers that can contribute to change dialogue with importers and brokers.[8]

Mirror trade statistics is an easy tool to use and comes at near zero cost. The skills requirements of mirror analysis are readily available for customs officers with basic analytical skills and already used to working with statistical or database management software. The data collection from both the local

systems and the United Nation's COMTRADE, as well as the training to acquire the ability to manage mirror trade statistics analysis only require a gentle learning curve (see Cantens (2015) for a step-by-step guide on computing trade gaps, interpreting various typologies and assessing potential revenue losses).

Mirror trade statistics is also important for risk management. Customs administrations have computer systems with selectivity modules that are based on fraud or risk profiles. But the objective (i.e. non-arbitrary) definition of these risk profiles requires a sound historical database from the results of the previous physical inspections, which is an issue when it comes to initiating a risk management strategy for a given customs administration. Moreover, risk management mostly must cope with situations where corruption is rampant, making the achievement of such sound historical databases on the feedback from previous controls difficult, eventually preventing the objective identification of new fraud patterns (Cantens, 2015). Mirror trade statistics indeed complements such risk analysis approaches by suggesting (additional) potential fraudulent trade flows patterns, relying on the use of external data instead of poorly reported internal data.

Moreover, sectoral studies are also being produced using mirror statistics to focus the controls on the riskiest operators and goods. Chalendard et al. (2016) used mirror trade statistics to identify and target products and sectors that were deemed risky in Madagascar, enabling the targeting of non-compliant customs operators.

Mirror trade statistics can be used for both frontline customs officers and investigation services. Mirror trade statistics may also be useful for post-clearance audits (PCAs) because it can be used as an objective way of flagging anomalies like tariff slippage, under or over valuation and origin fraud. Moreover, the average declared price for a commodity and declaration can easily be established and then compared with international prices or with any other information internally collected by tax administration. Such fraudulent flows may then be targeted during the PCA, where investigation teams have more time to deeply review the declared values and thereby enhance the effectiveness of audits.

As indicated by Cantens (2015), mirror trade statistics can initiate experimental fraud control systems, especially on major identified cases at both national and international level. Thus, mirror trade statistics can be conducted and lead to formation of some hypotheses on the suspected fraudulent trade flows and importer behaviour. Then, this can be cross-checked with experiences or observations of frontline customs officers on the ground. Eventually, this generates powerful and detailed leads to fraudulent trade flows to be targeted for audits and further investigations.

This approach was followed in Cameroon. As reported in Raballand et al. (2012), Cameroon Customs had closely monitored the trend in statistics gaps after having focused controls in some identified sectors and demonstrated that the strengthened control of some goods had led to decreased mirror statistics gaps.[9]

With a similar approach, Kalizinje (2018) employed mirror trade statistics in order to identify, classify and approximate customs revenue fraud in Malawi's 2015 trade data. The identified fraud was in the form of smuggling, misclassification, undervaluation and overvaluation. The analysis revealed plausible fraud cases in various products and this informed customs policies in risk analysis, enforcement and PCAs. A fraud control plan to help stop the identified customs revenue leakages was proposed.

Furthermore, in developed countries and according to WCO (2015), the Italian Customs and Monopolies Agency also employed mirror trade statistics to identify undervaluation of imported textiles from the Far East through the port of Naples. Through mirror trade statistics they were able to establish high-risk transactions, perform price analysis on international markets and use tools like technical analysis to identify threshold values and consider further examination. Since 2004, the Italian Customs and Monopolies Agency has realised an increase in the average declared values per kilogram. For instance, between 2003 and 2012 the average import value of textiles and related products increased by nearly four-fold.

Revelations on the possible quantitative assessments of customs fraud reinforces the enforcement strategy of customs administrations and helps in initiating a dialogue with economic operators and other relevant stakeholders like importers. By quantifying the extent of possible fraud and identifying the most likely sectors to fraud, it contributes to change dialogue with importers/brokers. After having identified possible fraudulent trade flows, customs administrations can engage relevant stakeholders.

4. A way forward?

Despite its usefulness, mirror statistics still suffer from some limitations that should be tackled in the future to make this approach even more effective. Four areas need to be kept in mind when Customs use mirror statistics for an operational purpose:

1. The use of mirror statistics is even more powerful when coordinated with other public agencies and private agents (e.g. tax department, company registry, social security institutions, banks, security forces, anti-corruption agencies). A coordinated inter-agency approach helps Customs to fight fraud more efficiently.

2. As explained by Raballand et al. (2009), mirror statistics are more useful when complemented with surveys and other methods of investigations. It is important to cross-check and investigate thoroughly with other sources of information to confirm fraud in a country.

3. It remains almost impossible to carry out mirror statistics analysis on a real-time basis due to reporting lags of exporters. Some real-time mechanisms of automatic exchange of information, like implemented in tax administrations in the world, should be replicated in Customs, probably with impetus from the WCO.

4. Mirror statistics use will be more powerful if packaged with a set of reforms regarding governance at the border, including human resource reforms that include better staff monitoring at the team and individual level (as was consequently implemented in Cameroon and Madagascar).

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Notes

1 Bilateral comparisons of two basic measures of a trade flow. It is a traditional tool for detecting the causes of asymmetries in statistics. For further details and explanations, see EUROSTAT (1998).

2 Papers using worldwide bilateral trade data at the highest level of internationally harmonised disaggregation (hs6) to model trade patterns from gravity equation have been typically using mirror data for their empirical estimates (e.g. Anderson & Van Wincoop, 2003; Carrère, 2006; Anson, Cadot & Olarreaga, 2006). Another well-known example of use of mirror data for solving such statistical issue is the database BACI provided by the CEPII (Gaulier, 2010), reconciliating both flows in a single one.

3 The accuracy of the declaration is critical for the importing country as declared value of imported goods is the tax base for the calculation of duties and taxes. Documentary or physical controls of the declaration might be consequently done by customs officers to verify its accuracy. On the other hand, exported goods are rarely taxed or controlled, which explains why the declarations of export might usually be considered less accurately filled.

4 This ratio can even reach 25 per cent for some landlocked countries but this is exceptional.

5 There are some valid explanations of statistics discrepancies, such as reporting period at the end of the year, some exchange rate conversion issues. However, Raballand et al. (2012) demonstrate how the possible explanations may not explain ratios of 100–200 per cent discrepancies or even more that were captured for some tariff lines in some countries worldwide.

6 Mirror statistics are easier to use for trade between developed and developing countries and is more difficult to use for neighbouring developing countries that share land borders because smuggling is the easiest between neighbouring developing countries (confirmed by Bensassi et al., 2016 in Mali and in Raballand et al., 2010 in Nigeria).

7 Harmonized system. The UN trade classification system.

8 Indirectly, mirror statistics may also contribute to data quality. The Common Market for East and Southern Africa (COMESA) pursues a statistics strategy that aims to ensure the availability of quality, timely and harmonised statistics in the regional bloc and, for instance in 2017, spearheaded a bilateral mirror merchandise trade statistics reconciliation workshop between Malawi and Zambia. The exercise was attended by representatives from national statistical offices and revenue authorities. In this task, mirror trade statistics was used to identify, process, explain and assess the causes of trade gaps between the two trading countries.

9 A similar trend was recorded in Madagascar with rice following the publication and dissemination of the paper written by Chalendard et al. (2016).

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Data mining in customs risk detection with cost-sensitive classification

Xin Zhou

Abstract

To improve the efficiency and accuracy of risk management in Customs, this paper explores the data mining process for risk detection with decision tree and boosting algorithms. The data are characterised by high dimensionality, imbalance and cost sensitivity. In particular, misjudging a false declaration as truthful can be more harmful than misjudging a truthful declaration as false. Therefore, considering the different costs of misclassification, we suggest taking a cost-sensitive approach with cost matrix in data mining. The inspection results are set as the prediction target variable to train the classifiers and make predictions. A data mining model of binary classification is formulated after feature selection and rebalancing. We evaluate its performance with classic measures of classification and customs risk assessment. The results show that the performance has been significantly improved with boosting while the output is less sensitive to cost-ratio under boosting.

1. Introduction

To ensure trade facilitation and safety, most customs administrations have developed risk management systems to identify potentially high-risk cargo and transport conveyances for closer scrutiny and inspection. With the application and integration of automated systems, customs risk management is becoming more reliant on the in-depth analysis of massive data. Customs in many countries have explored and implemented big data initiatives (Okazaki, 2017). Predictably, machine learning from historical data will be increasingly helpful for effective risk assessments and accurate targeting decisions.

In recent years, big data has become a key basis of business competition, and meanwhile, risk analysis based on data mining and machine learning are widely adopted by many industries (Mikuriya, 2016). For example, credit card companies have taken advantage of classification algorithms to identify possible fraud. Historical data are processed to train the model with the risk rate of the transactions as the target variable. The input variables are the attributes of transactions, such as the location, frequency and sum, as well as the main features of the applicants, such as gender, income and job. Therefore, the main features of high-risk transactions are analysed to detect potential fraud.

Similarly, Customs also face potential cases of fraud in declarations. Many customs administrations have explored risk profiling with various data mining methods, such as clustering (Hua et al., 2006), classification (Yaqin & Yuming, 2010), association (Laporte, 2011) and statistical scoring (Coundoul et al., 2012). Data mining allows Customs to identify the key risk indicators, to summarise the parameters from large databases and increase the accuracy of targeting. Thus, it can incorporate human expertise into machine learning, which can then determine the rules, which would not be able to be detected by human intuition and experience alone.

The decision tree is one of the most widely used algorithms for classification in data mining. It can process both numerical and non-numerical data. Its outcomes are highly accurate and efficient and, importantly, easily interpreted, which is crucial for Customs. In this study, we apply the C5.0 classification algorithm with boosting to risk detection, recognising that single weak classifiers can be strengthened by 'boosting' to reduce the bias and variance of the model.

Generally, for classification modelling, two types of errors—false positive and false negative—are considered with the same impact. However, regarding risk detection in Customs, misclassifying fraudulent declarations as legitimate (FN, false negative) has more serious consequences than misclassifying legitimate declarations as fraudulent (FP, false positive). In view of this, this paper builds the data mining model with cost-sensitive learning, which allows the variation of costs for different misclassification types. The performance of the model is then discussed under varied cost ratios of the two types of misclassification. Note that the term 'classification' in this paper is used generically, not in the context of tariff classification.

2. Characteristics of customs data

2.1 High dimensionality

In most countries, there are many data elements to declare to Customs, such as consigner/consignee, loading/unloading port and cargo information. When these data are linked with inspection records and the enterprise's financial information, the resultant dataset is particularly high dimensional. While there is more information in high-dimensional datasets, it is not necessarily desirable for data mining, as high dimensionality may include irrelevant features and 'noise' that makes it difficult to understand and visualise the outcome of the model. Moreover, the amount of time and memory required for computing could be enormous (Tan et al., 2005).

Therefore, to reduce the high dimensionality, it is necessary to undertake a feature selection prior to data mining. Feature selection, also known as attribute selection, is the process of selecting a subset of relevant features (variables, predictors) to be used in model construction. Generally, feature selection chooses key fields and filters unrelated or repeated fields, relying on both selection algorithms and human expertise. The common selection algorithms include principal component analysis (PCA), linear regression and Pearson correlation coefficient.

2.2 Imbalanced class distribution

Most transactions are declared truthfully to Customs but others are declared falsely. For instance, the ratio of true and false declarations is 82.73 per cent to 17.27 per cent in the dataset of this study. This implies an imbalanced class distribution among the customs dataset. It means the likelihood that one class is represented by a large quantity of sample declarations, while the other one is represented by only a few. Standard classifiers generally perform poorly on imbalanced datasets and pay less attention to the smaller class. Classification rules that predict the small class tend to be fewer and weaker than those that predict the prevalent class (Sun et al., 2006).

For this reason, data rebalancing is indispensable if Customs is to avoid misclassification when detecting the false declarations, which are samples of a small class. The most common methods of rebalancing are oversampling and undersampling (Tan et al., 2005; Chawla et al., 2011; Sug, 2011).

Oversampling is a method to get more data by replicating existing data samples with fewer classes of data. Undersampling refers to balancing the number of different categories of data samples by reducing the number of classes of existing data samples. However, random undersampling and oversampling methods have their own shortcomings. The undersampling method can potentially remove certain

important examples, while oversampling can lead to overfitting (Chawla, 2005). In practice, models after rebalancing are more likely to provide a higher identification rate on the rare category. With imbalanced class distribution, the data mining for customs risk profiling could rebalance the data at the beginning. However, the degree of rebalancing varies in different applications.

2.3 Cost-sensitive classification

In the two-class scenario, samples can be categorised into four groups after the classification process is denoted in the confusion matrix. This study adopts the two-class classification for customs risk detection, assuming that the predicted positive declarations are considered to be of high risk and inspected, while the predicted negative declarations are considered of low risk and released. The confusion matrix is presented in Table1.

Table 1: Confusion matrix of 2-class classification for customs risk detection

		Predicted class	
		Predict positive – inspected	**Predict negative – released**
Actual class	**False**	False declaration inspected (True positives, TP)	False declaration released (False negatives, FN)
	True	True declaration inspected (False positive, FP)	True declaration released (True negatives, TN)

In this two-class classification model, there are two types of errors: false negative (FN) and false positive (FP). False negative (FN) refers to the false declarations that are wrongly released. False positive (FP) refers to the true declarations that are unnecessarily inspected. Obviously, the actual losses of different types of misclassification are different. Take the bank's loan business for instance, it will incur much higher costs when misjudging an 'actual bad' as an 'actual good' than misjudging an 'actual good' as an 'actual bad'. Similarly, regarding risk detection in Customs, the consequences of misjudging a false declaration as legitimate are much more serious than misjudging a true declaration as a fraudulent one. Therefore, customs risk detection could be categorised into the cost-sensitive decision-making process, where different misclassification errors incur different costs.

In view of this, the cost-sensitive classification technique can be introduced to generate a model that has the lowest cost (Elkan, 2001). Therefore, the classifier can cover more positive examples, although at the expense of generating additional false alarms. The cost matrix for custom risk detection is provided in Table 2. The cost of committing a false negative error is denoted as Cost (A), and the false positive error is denoted as Cost (B). The cost of correct classifications—true positive and true negative—are both set to be zero.

Table 2: The cost matrix for custom risk detection

		Predicted class	
		Predict positive – inspected	**Predict negative – released**
Actual class	**False**	0	Cost (A)
	True	Cost (B)	0

According to the previous assumption that all the positive predictions are inspected, higher Cost (A) will lead to a larger proportion of positive predictions, that is, the rate of inspection will increase. So that the cost matrix could be set according to the target inspection rate and the detective rate (successfully seized rate). As a result, the ratio of Cost (A) and Cost (B) in the cost matrix in Table 2 is basically the trade-off between trade security and facilitation. For the purpose of detecting high-risk commodities such as drugs, the ratio should be significantly higher. In contrast, if it is for general risk profiling of regional declarations, the ratio could be adjusted under the constraints of limited inspection resources.

3. Decision tree and boosting

3.1 Decision tree

A decision tree is a classic learning method in machine learning. A decision tree is a tree structure in which each internal node represents a prediction about an attribute, each branch represents the output of a prediction, and each leaf node represents an output of classification with inference rules. Compared to other classification algorithms, the decision tree uses a white box model, so its rule set is simple to understand and interpret.

The decision tree belongs to supervised learning. In supervised learning, each example in the training data set is a pair consisting of an input object and a desired output value, and supervised learning analyses the training data and produces an inferred function, which can be used for mapping new examples. A decision tree is obtained by learning the input samples and determining the classification of the new data. Commonly used decision-tree algorithms include ID3, C4.5, C5.0, CART and Quest.

3.2 C5.0 Algorithm

C5.0 algorithm is a descendent of the C4.5 machine learning algorithm. It is derived from an earlier system called ID3. The C5.0 model works by splitting the sample based on the field that provides the maximum information gain. Each subsample defined by the first split is then split again, usually based on a different field, and the process is repeated until the subsamples cannot be split any further. Finally, the lowest level splits are re-examined, and those that do not contribute significantly to the value of the model are removed or pruned (Thombre, 2012).

Compared to the C4.5 algorithm, the advantages of the C5.0 algorithm are obvious: it is faster, and its memory usage is more efficient than C4.5. C5 gets smaller decision trees and generates more accurate rules (Pandya & Pandya, 2015). In particular, it supports boosting, which is a process of generating several decision trees, which are combined to improve the predictions (Pang & Gong, 2009).

3.3 Boosting

Boosting is an ensemble method that combines the performance of a set of weak classifiers to produce a single strong classifier. Boosting refers to a general and provably effective method of producing a very accurate prediction rule by combining rough and moderately inaccurate rules of thumb in a manner similar to that suggested above (Freund & Schapire, 1996; 1997). Boosting works by repeatedly running a given weak learning algorithm on various distributions over the training data, and then combining the classifiers produced by the weak learner into a single composite classifier. Generally, combining multiple classifications can reduce the bias error (Kittler, 1998).

The boosting approach starts with a method or algorithm for finding the rough rules of thumb. The boosting algorithm calls this 'weak' or 'base' learning algorithm repeatedly, each time feeding it a different subset of the training examples. Each time it is called, the base learning algorithm generates a new weak prediction rule. Boosting assigns a weight to each training example and may adaptively change the weight at the end of each boosting round. After many rounds, the boosting algorithm must combine these weak rules into a single prediction rule that, hopefully, will be much more accurate than any one of the weak rules (Schapire, 1999; 2002).

4. Evaluation measures

Evaluation measures play a crucial role in both assessing the classification performance and guiding the classifier modelling. In this study, the performance of the model is evaluated with both classic measures of classification and customs risk assessment, as follows:

(1) Inspection rate

Taking the positive prediction as high risk to be inspected, the inspection rate can be derived as the percentage of the positive predictions in all training samples

$$\text{Inspection rate}=\frac{TP+FP}{TP+TN+FP+FN}$$

(2) Accuracy

Accuracy is defined as the percentage of the number of correct predictions in total number of predictions.

$$\text{Accuracy}=\frac{TP+TN}{TP+FP+TN+FN}$$

However, for classification with the class imbalance problem as mentioned above, accuracy is no longer a proper measure since the rare class has very little impact on accuracy as compared to the prevalent class. For example, in a problem where a rare class is represented by only 10 per cent of the training data, a simple strategy can be adopted to predict the prevalent class label for every example. It can achieve 90 per cent accuracy.

(3) Precision-detection rate

Precision determines the fraction of records that turn out to be positive among the predicted positive class (Tan et al., 2005). The definition of precision is given below.

$$\text{Precision, } p=\frac{TP}{TP+FP}$$

In customs risk-detection modelling, if it is assumed that the false declaration can be seized after inspection, the detection rate of inspection is equivalent to the precision above.

(1) Recall

Recall measures the fraction of positive examples correctly predicted by the classifier (Tan et al., 2005). Classifiers with a large recall have very few positive examples misclassified as the negative class. Recall is also defined as true positive rate:

$$\text{Recall, } r = \frac{TP}{TP + FN}$$

In this study, we assume that all the predicted positive examples are targeted and inspected, thus recall means the fraction of inspected examples among all the false declarations.

(2) F_1 measure

In practice, there is a trade-off between the precision and recall values. For example, if we predict all the examples as positive, then recall will be perfect, but with a very poor precision value. Precision and recall can be summarised into a F_1 measure, which represents a harmonic mean between recall and precision

$$F_1 \text{ measure} = \frac{2rp}{r + p}$$

(3) AUC

The area under a ROC (receiver operating characteristic) curve (AUC) provides a single measure of a classifier's performance for evaluating which model, on average, is better. The AUC value is equivalent to the probability that a randomly chosen positive example is ranked higher than a randomly chosen negative example.

In this study, we use the above evaluation measures to compare and improve the data mining model for custom risk detection.

5 Classification model for risk detection with cost sensitivity

5.1 Data understanding and preparation

We employ the C5.0 decision tree algorithm in IBM SPSS Modeler to analyse data in the study. SPSS Modeler provides an intuitive graphical interface to help visualise each step in the data mining process as part of a stream and offers multiple machine learning techniques, including classification.[1] In this study, the classification model is trained by the historical declaration data of China Customs. The dataset contains 30,000 records, and all these records are inspected declarations. According to the results of inspection, 82.73 per cent of the records are negative, referring to true declarations, and 17.27 per cent of records are positive, referring to false declarations. Remarkably, we suggest training the model with the data of inspected declarations instead of the whole dataset of all declarations including the declarations released without inspection. This reason is that, the declarations released without inspection are tagged as negative, but it may turn out to be actual positive instead.

Besides the inspection result, the dataset has 21 attributes, including the name and description of the goods, modes of transportation, country of origin, HS code, mode of trade, unit, quantity, gross weight, number of packages, unit price, total price, currency, as well as the information of the operator, such as credit class, province, region, type, industry, the registered capital, currency and registered time.

According to the inspection results, the declarations are assigned into two categories: positive and negative, tagged as type 1 and type 0. HS code and country of origin are transformed into HS chapter

and continent. The name and description of the goods are excluded because they are both strings of text, and text mining is not involved in this study. After the transformation, the inspection result is set as target variable, and the other attributes are set as predictive variables.

5.2 Feature selection

Confronted with the high dimensionality of this modelling, we use Pearson Chi-square to select the main features from predictive variables. Pearson Chi-square tests for the independence of target variable and the predictive variables without indicating the strength or direction of any existing relationship. If the correlation between predictive variables and target variables is relatively strong, the impact of predictors on target variables will be significant and show high importance values.

After the independence between the target and the predictive variables was tested, the predictive variables were sorted with importance value. In this case, it turned out that the importance values of the 15 predictive variables were higher than 0.9^2, as shown in Table 3. We removed the unimportant variables with the importance value under 0.9 and remained the remaining 15 variables as input variables for data mining.

Table 3: The importance values of predictive variables

Predictive variables	Importance value	Input or not
Mode of trade	1	Y
Origin country	1	Y
HS chapter	1	Y
Mode of transportation	1	Y
Unit	1	Y
Province of the operator	1	Y
Industry of the operator	1	Y
Types of the operator	1	Y
Continent of the origin country	1	Y
Credit class of the operator	1	Y
Registered time of the operator	1	Y
Gross weight	1	Y
Quantity	0.999	Y
Unit price	0.921	Y
Total price	0.904	Y
Registered capital of the operator	0.611	N
Number of packages	0.315	N

5.3 Data partition and balance

The data were partitioned into training and testing data, with 70 per cent of the data set to train and the remaining 30 per cent to test. The proportions of the positive class (tagged as '1') and the negative class (tagged as '0') were17.4 per cent and 82.6 per cent in both the training and testing set, as is shown in Figure 1.

The distribution of the dataset explored (82.73% negative and 17.27% positive) indicated that a relatively balanced distribution attains a better result. However, it does not mean that the ratio of sample size of small class to the prevalent class should be 1:1. At what imbalance degree the class distribution deteriorates the classification performance varies in different applications. We used oversampling to balance the data and compared the classification performances of decision trees with different ratios. Considering the possible over fitting, we chose to double the sample size of positive class in the training dataset.[3] For the purpose of evolution, the class distribution in the testing dataset remained the same as the initial data. After balancing, the proportions of the positive class (tagged as '1') and the negative class (tagged as '0') were changed into 29.4 per cent and 70.4 per cent in training dataset. Meanwhile, the positive class remained at 17.4 per cent and the negative class at 82.6 per cent in the testing set for the sake of evaluation, as is shown in Figure 1.

Figure 1: Partitioned sample sizes before and after balancing

5.4 Primary decision tree model

After the data preparations above, we trained the primary decision tree model with the following parameter setting. The pruning severity was 75 per cent.[4] The ratio of Cost (A) and Cost (B) was 1:1, where the former was the cost of committing a false negative error and the latter was the cost of false positive error. Cross-validation with ten folders was applied to ensure the reliability of the model. Part of the decision tree generated is shown in Figure 2 and classification results of the primary model are shown in Tables 4–6.

Figure 2: The decision tree generated (partial)

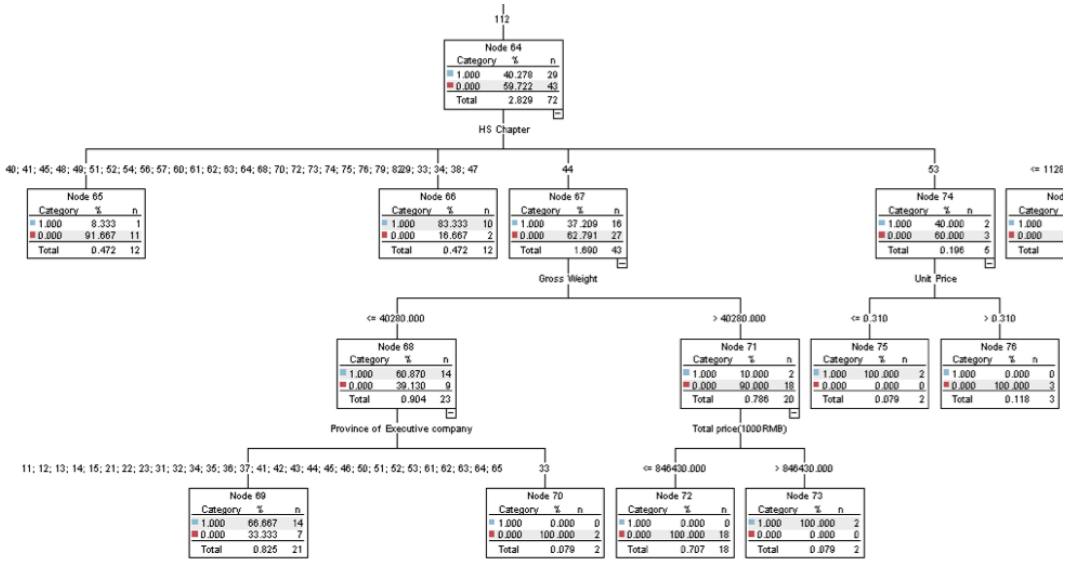


Table 4: The classification results of the primary model in training data

		Predictive class		Sum	Correct samples	Accuracy
		1	0			
Actual class	1	4,498	2,802	7,300	4,498	61.62%
	0	517	16,788	17,305	16,788	97.00%
Sum				24,605	21,286	86.51%

Table 5: The classification results of the primary model in testing data

		Predictive class		Sum	Correct samples	Accuracy
		1	0			
Actual class	1	775	800	1575	775	49.21%
	0	187	7283	7470	7283	97.50%
Sum				9045	8058	89.09%

Table 6: AUC and Gini of the primary model

	AUC	Gini
Training	0.882	0.764
Testing	0.836	0.673

Generally, the accuracy in training data is supposed to be higher than that in testing data; however, in our experiment it was not so. The accuracy in training data was 86.51 per cent while it was 89.09 per cent in testing data. However, this does not mean the performance was worse in training data as AUC, Gini and the accuracy of positive class were higher in training data. This result proves that AUC is a better measure than accuracy for evaluating and comparing classifiers.

The AUC value in testing data was 0.836, which was acceptable. As shown in the previous section, the accuracy of 89.09 per cent was less meaningful here, because in imbalanced data such as this, it could be 82.6 per cent if all the examples were predicted to be negative.

Overall, the model performed well in predicting the negative class with an accuracy of 97 per cent, but its performance was not satisfactory when dealing with the positive class because the accuracy dropped sharply to 49.21 per cent. The results suggested that the model needed to be optimised.

5.4 Boosting

In this study, we applied boosting with 10 trials. With the iteration of ten trials boosting, the model would generate ten trees and ten sets of rules. Each tree was a weak classifier and then ten trees were formed into a strong classifier after boosting. The classification results with boosting are shown in Tables 7–9.

Compared to the primary model in Tables 4–6, the performance of the classifier was significantly improved after boosting. The overall accuracy and AUC were increased from 89.09 per cent to 94.1 per cent respectively and 0.836 to 0.982 in testing data. For the prediction of the positive class, the accuracy was also raised from 49.21 per cent to 71.57 per cent, while the prediction of the accuracy in the negative class was 98.94 per cent. The classifier with boosting achieved satisfactory results.

Table 7: The classification results with boosting in training data

		Predictive class		Sum	Correct samples	Accuracy
		1	0			
Actual class	1	6536	764	7300	6536	89.53%
	0	229	17076	17305	17076	98.68%
Sum				24605	23612	95.96%

Table 8: The classification results with boosting in testing data

		Predictive class		Sum	Correct samples	Accuracy
		1	0			
Actual class	1	1120	455	1565	1120	71.57%
	0	79	7391	7470	7391	98.94%
Sum						94.1%

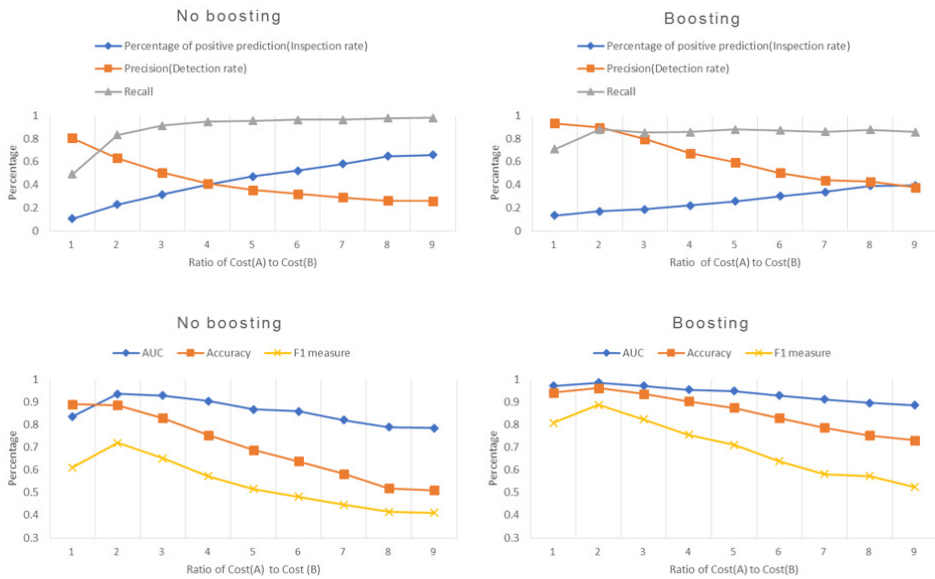
Table 9: AUC and Gini of the primary model

	AUC	Gini
Training	0.991	0.971
Testing	0.982	0.943

5.5 Cost-sensitive analysis

As discussed in the above section, risk detection in Customs is cost sensitive and, in this study, the cost of false positive, Cost (B), was set as the baseline. The ratio of Cost (A) and Cost (B) was set above one. The results of the decision tree models were compared with the variation of cost ratio, with and without boosting. We tried to explore (1) how the ratio change impacts the classifiers' performance; and (2) whether boosting is able to improve the performance on positive class with varied cost ratios.

Figure 3: The performance of the models with the variation of cost ratio



With the increase in the cost ratio, the percentage of positive prediction (inspection rate) increased with or without boosting, which proved the trade-off between trade security and facilitation, but precision (detective rate) decreased. Without boosting, the recall rate also increased with the growth of cost ratio, which indicated that more positive samples were targeted as the result of the higher inspection rate. This also showed the trade-off between recall and precision.

When boosting was applied, recall increased due to the change of cost ratio from 1 to 2. However, recall remained almost the same when cost ratio changed from 3 to 9. With similar inflection point, other metrics such as AUC, accuracy and F_1 measure improved when cost ratio increased from 1 to 2 (only except the accuracy without boosting and declined as cost ratio changed from 3 to 9).

In summary, we have come to the following conclusions:

(1) Overall, the performance of the classifiers is satisfactory regardless of the cost ratio. However, multiple rule sets will be generated with boosting, which can be too complicated to understand and interpret.

(2) The evaluation measurements with or without boosting, have different sensitivity to cost ratio. With boosting, the evaluation measurements are less sensitive to ratio variation. In contrast, without boosting, the evaluation measurements are more sensitive to ratio variation. In particular, the recall rate increases with the cost ratio without boosting. This could be applied to risk detection when a high recall rate is required, such as drug smuggling.

(3) The performance has an inflection point with the growth of cost ratio. The evaluation measurements are not changed linearly with the growth of cost ratio. After the inflection point, the performance of the classifiers will be significantly reduced as the cost ratio is raised.

The conclusions above are also reflected in Figures 4–5, which demonstrate the distributions of predictive classes under the same actual class, when the cost ratio varies in 1, 2, and 3 with or without boosting. Given a cost ratio, there are two rows that represent the sample size of actual class, tagged as '1' and '0'. The left part in the row of actual 1 indicates true positive predictions (TP), while the rest indicates false negative predictions (FN). Similarly, the left part in the row of actual 0 indicates false positive predictions (FP), while the rest indicates true negative predictions (TN).

It also shows that when boosting is not applied, the positive predictions increase with the growth of cost ratio. More true positive predictions (TP) are covered, but meanwhile, false positive predictions (FP) also grow dramatically. In contrast, when the cost ratio builds up from1 to 2, the true positive predictions (TP) rises while false positive predictions (FP) slightly increased. As shown above, the predictions of the classifier with boosting are less sensitive to the change of cost ratio.

Figure 4: The distributions of predictive classes without boosting

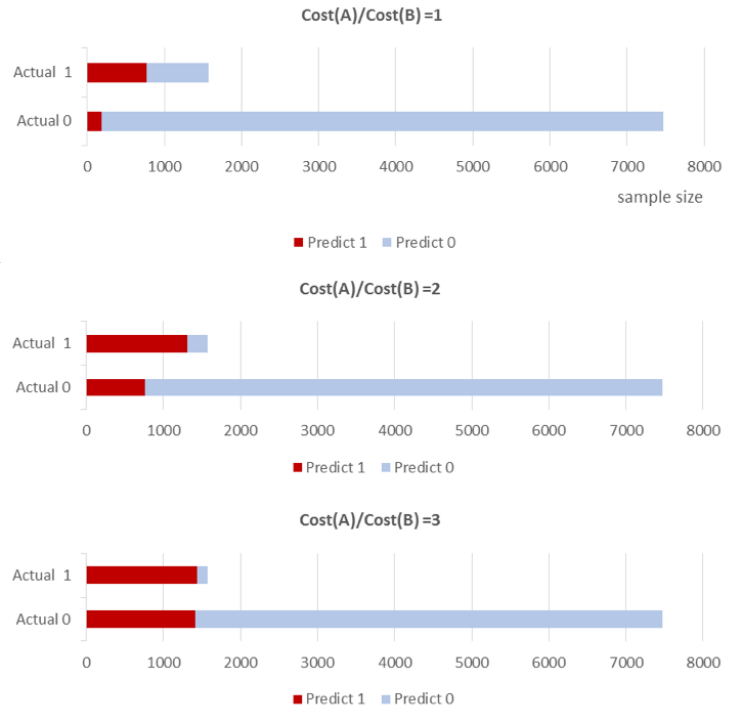
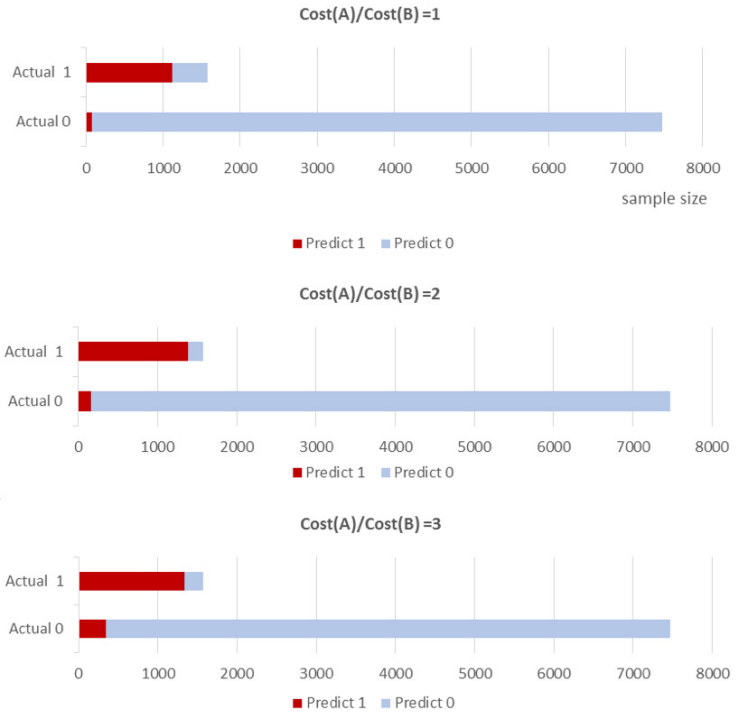


Figure 5: The distributions of predictive classes with boosting



6. Conclusion

This paper demonstrates the data mining process with a decision tree algorithm. We conclude that customs data have the characteristics of high dimensionality, imbalance, and cost sensitivity. In view of this, a data mining model of binary classification is investigated and the interactive influences of cost sensitivity and boosting on performance of the classifiers are discussed by comparing the output change with parameter adjustment. It has been proved that the model with boosting can achieve an ideal classification performance. Ultimately, this paper aims at providing a process of data mining modelling and the way of parameter adjustment, rather than the optimal values of parameters. The reason for this is that the optimal values of parameters may vary in different data applications, even for the same model.

The following research issues are open for future investigation:

(1) In this study, the positive records in the data set are combined with different types of non-compliance. If these records are segmented, according to the risk types, such as drug smuggling, price understating, or high-risk commodity, the model can generate a more specific rule set.

(2) The name and description of the goods are excluded in this study because they are both strings of text. Text mining can be explored in the future research, which can extract more information and cross-validate the data.

Overall, this study explored data mining in risk detection of Customs. With tremendous potential for applications, data analysis and machine learning will continue to receive more attention and play irreplaceable roles in customs administrations. It is worth pointing out that data mining for customs risk detection is not a one-time solution. In order to achieve a stable performance, the dataset should be updated regularly, and the parameters need maintaining constantly.

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Notes

1. For more information on C5.0 node of IBSS SPSS modeler, please refer to the website: https://www.ibm.com/support/knowledgecenter/en/SS3RA7_15.0.0/com.ibm.spss.modeler.help/c50node_general.htm
2. According to the output of IBM SPSS Modeler, the importance value is considered to be important when it is above 0.95, to be marginal when above or equal to 0.9, and to be unimportant under 0.9.
3. The results showed that the performance would improve significantly if the sample size of the positive class was doubled or tripled. However, there was only a slight improvement from the doubling to the tripling. To avoid over fitting, we chose to double the sample size of positive class in the training dataset.
4. Generally, it is proper to set pruning severity from 70% to 80%. We compared the results of the model respectively when it ranged from 65%, 70%, 80% and 85%. After comparing the measures of recall, accuracy and tree depth, we chose the pruning severity of 75%.

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WORLD CUSTOMS ORGANIZATION

Section 3

Special Report

World Customs Journal Special Edition – PICARD Conference 2020

Publication of a special edition of the *World Customs Journal* will coincide with the 2020 World Customs Organization (WCO) Partnership in Customs Academic Research and Development (PICARD) Conference, which is being jointly organised by the WCO and International Network of Customs Universities (INCU). The overall theme of the special edition will be 'WCO and the customs and trade community, past and future'.

The special edition will have two sub-themes, with the following general scope:

1. WCO impact to date and lessons learnt:

- The work/achievements of the WCO and the practical ways in which it has supported member administrations and the international trading community since its inception.
- What lessons have been learnt on the role and functioning of the WCO in relation to developments in the customs community during the last 20 years?
- How has the WCO contributed to the evolution of the customs mission and the implementation of international agreements since its inception?
- Has the role of Members, donors, international governmental organizations and international associations of private stakeholders changed at the WCO?
- How has WCO and academia cooperated to improve the capacities of customs and promote customs topics in research agendas? What has the WCO PICARD Programme achieved to date? Has it met its objectives? Has it fulfilled stakeholders' expectations? To what extent has it linked in with other WCO capacity-building initiatives?

2. WCO future directions:

- Since the creation of the WCO, the nature of borders and border management has evolved. For example, the mission of some customs administrations has seen the addition of security and migration control, and trade facilitation is emerging as a key global issue. Are we still in the same paradigm as in the 1950s from the perspective of borders and international trade? How is the evolution impacting the functioning of the WCO and the way in which administrations are represented at WCO? Are WCO Members' expectations evolving regarding the WCO functioning and deliveries?
- The nature of 'international instruments' was the law. Is it still the case? Aren't rules more 'flexible', practical, based on data, facts? Are we in a 'peer governance', a more diffuse governance rather than the usual top-down one that particularly fits with the existing structure and work of international organisations? Are we still governed by rules and legal norms when we see the influence of Doing Business, governance by data and the increase of public participation and influence in policy making processes (even through 'populism', new media...)?
- The relevance and future of the WCO PICARD Programme. What are the stakeholder expectations? Is there a need for a new PICARD Strategy (from the perspective of both research and education)?
- How do we ensure that the PICARD strategy is consistent with other WCO initiatives such the competency framework, career path development, etc.?

- The policy drivers of Customs that influence the mission and objectives of customs administrations from a political perspective. How does this impact the administration of Customs at the national, regional and international level, and in turn the role of the WCO?
- Customs from a strategic (as opposed to the more traditional administrative) point of view, including customs direction of travel. This topic could explore issues like leadership in customs as well as customs policy vs customs administration.
- Are developments in technology impacting customs and the WCO from different perspectives, particularly in the context of data-driven governance? What impact will this have in the coming decades?
  - › Will data and machines increasingly drive policy formulation and initiatives, and guide and evaluate the effectiveness and efficiency of customs administration?
  - › How can Customs leverage new and emerging technologies to support their management of risk?
  - › Do we need new approaches to boost innovation in customs technologies and solutions? Customs administrations are major users of diverse type of technologies including detection technologies, laboratory equipment, risk management software, etc. Are these technologies developed based on the real challenges and needs of Customs?
  - › To what extent are customs administrations collaborating with the private sector in the development of better performing and more tailored solutions? Do open innovation and user innovation strategies – widely exploited by firms for new product development – present opportunities to contribute to the development of new products and services that support customs administrations?
- Future of the Revised Kyoto Convention and an ongoing RKC review process. An article based on previously published short article in the WCO News, but more detailed and with an academic approach.
- A compilation of edited interviews with leaders in our field, each answering very specific questions about where customs is heading.

Contributors

Approximately 20 articles will be chosen for publication. Authors will be selected by way of a dual process – specific people are being invited to contribute articles to this edition and, in addition, a general call for papers is being made. Contributions are being sought from across the following groups:

- WCO
- Customs administrations
- Private sector
- Academia.

It is anticipated that a formal call for papers will be jointly issued by the WCO and INCU in November 2019.

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Section 4

Reference Material

Guidelines for Contributors

The *World Customs Journal* invites authors to submit papers that relate to all aspects of customs activity, for example, law, policy, economics, administration, information and communications technologies. The Journal has a multi-dimensional focus on customs issues and the following broad categories should be used as a guide.

Research and theory

The suggested length for articles about research and theory is approximately 5,000 words per article. Longer items will be accepted, however, publication of items of 10,000 or more words may be spread over more than one issue of the Journal.

Original research and theoretical papers submitted will be reviewed using a 'double blind' or 'masked' process, that is, the identity of author/s and reviewer/s will not be made known to each other. This process may result in delays in publication, especially where modifications to papers are suggested to the author/s by the reviewer/s. Authors submitting original items that relate to research and theory are asked to include the following details separately from the body of the article:

- title of the paper
- names, positions, organisations, and contact details of each author
- bionotes (no more than 100 words for each author) together with a recent, high resolution, colour photograph for possible publication in the Journal
- an abstract of no more than 100 words for papers up to 5,000 words, or for longer papers, a summary of up to 600 words depending on the length and complexity of the paper.

Please note that previously refereed papers will not be refereed by the *World Customs Journal*.

Practical applications, including case studies, issues and solutions

These items are generally between 2,000 and 5,000 words per article. Authors of these items are asked to include bionotes (no more than 100 words for each author) together with a recent, high resolution, colour photograph for possible publication in the Journal. The Editorial Board will review articles that relate to practical applications.

Reviews of books, publications, systems and practices

The suggested length is between 350 and 800 words per review. The Editorial Board will review these items submitted for publication.

Papers published elsewhere

Authors of papers previously published should provide full citations of the publication/s in which their paper/s appeared. Where appropriate, authors are asked to obtain permission from the previous publishers to re-publish these items in the *World Customs Journal*, which will acknowledge the source/s. Copies of permissions obtained should accompany the article submitted for publication in the *World Customs Journal*.

Authors intending to offer their papers for publication elsewhere—in English and/or another language—are asked to advise the Editor-in-Chief of the names of those publications.

Where necessary and appropriate, and to ensure consistency in style, the editors will make any necessary changes in items submitted and accepted for publication, except where those items have been refereed and published elsewhere. Guidance on the editors' approach to style and referencing is available on the Journal's website.

Letters to the Editor

We invite Letters to the Editor that address items previously published in the Journal as well as topics related to all aspects of customs activity. Authors of letters are asked to include their name and address (or a pseudonym) for publication in the Journal. As well, authors are asked to provide full contact details so that, should the need arise, the Editor-in-Chief can contact them.

All items should be submitted in Microsoft Word or RTF, as email attachments, to the Editor-in-Chief: **editor@worldcustomsjournal.org**

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