

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

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## Abstract

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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.

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## 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 based 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.<sup>1</sup>

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-arbitrary 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 |
|             | Offence    | 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<sup>2</sup>:

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.

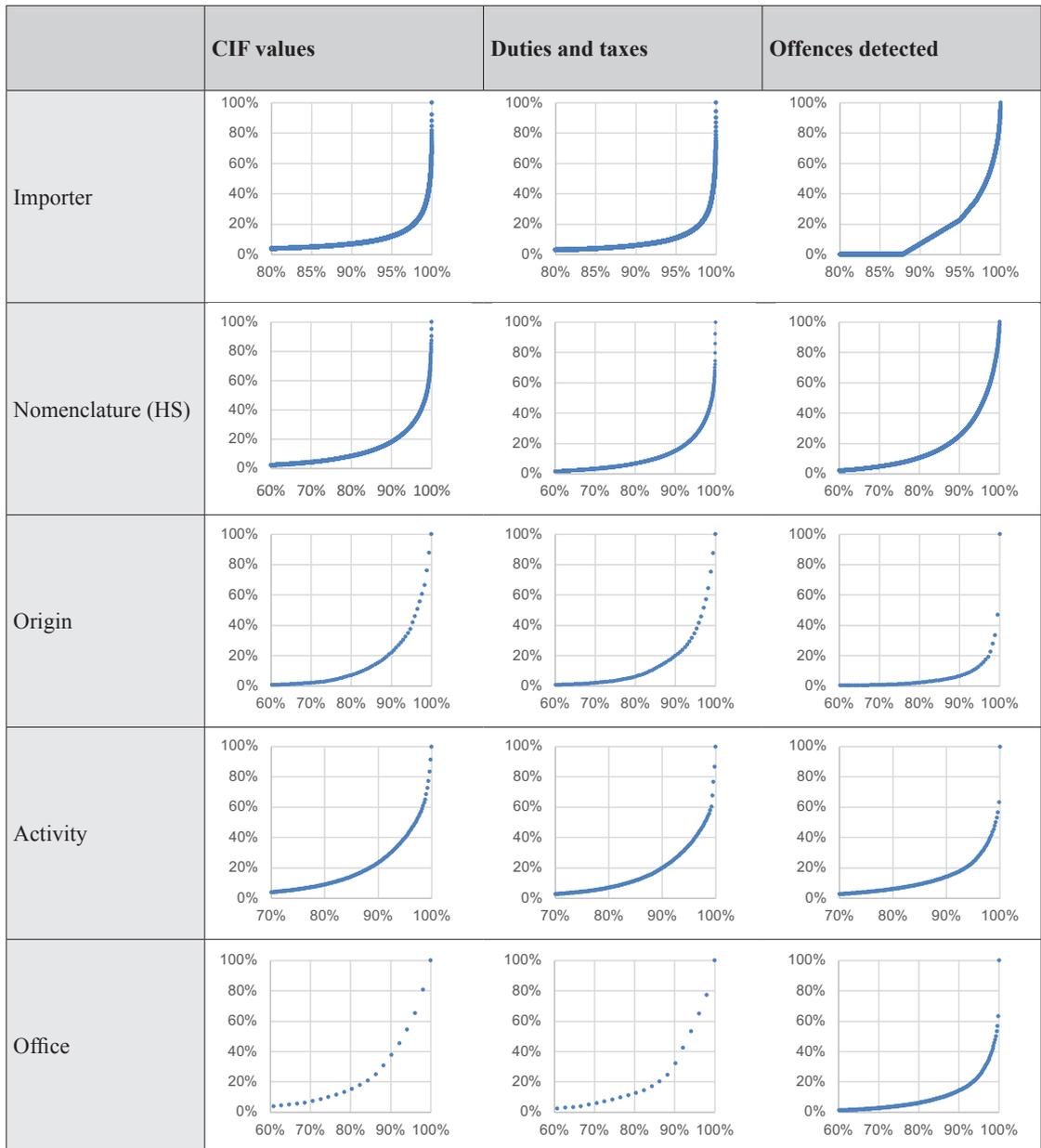
*Table 2: Criteria for predicting fraud – 100,000 observations*

| 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.<sup>3</sup>

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:

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

$P(Y = 1)$  is the probability that the declaration is non-compliant,  $\Phi$  is the distribution function of the normal rule.  $X_{1i}, X_{2i}, \dots, X_{ni}$  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,  $\beta_1, \beta_2 \dots \beta_n$  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***<br>(0.032)  |
| Nomenclature  | 1.19***<br>(0.05)   |
| Origin  | 1.8***<br>(0.08)    |
| Port of entry   | 0.97***<br>(0.068)  |
| Activity  | 0.72***<br>(0.66)   |
| Constant  | -4.18***<br>(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         |
| <b>Total</b>   | <b>88.0</b>     | <b>12.0</b> | <b>100.0</b> |

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**

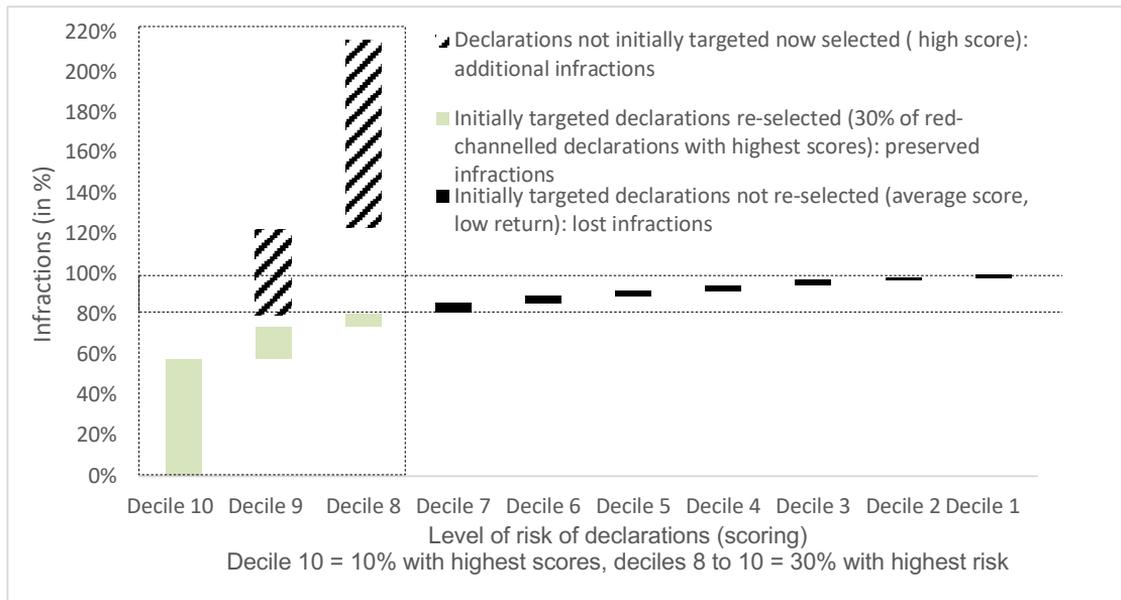
In order to make simulations, the set of declarations have been split in two subsamples. The declarations of the first half of 2016 were used to calibrate the model before computations and simulations are performed over the declarations of the second half of 2016. The simulated selectivity of controls 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.<sup>4</sup>

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.

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.

### Christopher Grigoriou



Christopher Grigoriou joined the CERDI, University of Auvergne, in 2007 as Associate Professor in Economics and Econometrics. Currently on leave, he is working in Geneva as a consultant, in particular for international institutions like IMF or World Bank for customs and tax administrations matters, at the crossroad of international trade and public finance. He is also an invited professor at the Swiss Graduate School of Public Administration (IDHEAP, Lausanne University) where he teaches econometric modelling in the field of public finance. He holds a PhD in economics at the CERDI (2006). He is currently doing research on international trade, illicit cross-border trade measurements and risk management for government services.