Risk management systems: using data mining in developing countries' customs administrations

Bertrand Laporte

Abstract

Limiting intrusive customs inspections is recommended under the revised Kyoto Convention, and is also a proposal discussed as part of World Trade Organization (WTO) trade facilitation negotiations. To limit such inspection, the more modern administrations intervene at all stages of the customs chain using electronic data exchange and risk analysis and focusing their resources on *a posteriori* controls. Customs administrations of developing countries are slow to move in that direction. Risk analysis would therefore seem to be a priority for modernising the customs systems in developing countries. The most effective risk management system uses statistical scoring techniques. Several simple statistical techniques are tested in this article. They all show a good capability to predict and detect declarations that contain infractions. They can easily be implemented in developing countries' customs administrations and replace the rather inefficient methods of selectivity that result in high rates of control and very low rates of recorded infractions.

Introduction

Limiting intrusive customs examinations is recommended under the revised Kyoto Convention. It is also a proposal discussed in the context of World Trade Organization (WTO) trade facilitation negotiations. To limit these intrusive examinations, the more modern governments now intervene at all stages of the customs chain, using electronic data exchange and risk analysis, and focusing their resources on *a posteriori* inspection (Revised Kyoto Convention 1999; Keen 2004; eds De Wulf & Sokol 2004).

Developing countries' customs authorities are slow to move in this direction and implement the latest risk analysis and management techniques (Geourjon & Laporte 2005; Geourjon, Laporte & Rota Graziozi 2010). These techniques are used in many areas which are facing the risk of fraud, for example, in insurance, credit banking, and so on (for a review, see Bolton & Hand 2002; Phua et al. 2005). Yet risk analysis is a priority for modernising customs in developing countries. Indeed, it is a powerful lever for conducting a comprehensive operational reform in particular because it calls for closer cooperation between different departments in charge of information management and also because it allows for the redeployment of agents to *a posteriori* inspection. Risk analysis should be accompanied by a reform in human resource management, with recruitment on the basis of job profiles and specific skills.

Most developing countries have outsourced risk management systems to private inspection companies when implementing pre-shipment inspection programs and/or scanning services. The systems offered by these companies work only for imports/exports that depend on their contractually-defined scope of intervention. Their effectiveness is often compromised by a limited exchange of information with customs authorities (Johnson 2001). For imports/exports falling within customs intervention, risk management systems are based on simple criteria of selectivity – most often as blacklists focusing on the goods, the origin of the goods and the importer, plus a random target. This risk management system has not proven to be particularly effective. It requires customs authorities to monitor intrusively a large number of containers which, as identified in unpublished technical reports, frequently results in recorded offence rates of less than 3 per cent in the cases of Benin, Côte d'Ivoire, Mali and Senegal.

Selectivity as a risk management method was forced on many countries as a result of using the integrated customs clearance management system, ASYCUDA (**A**utomated **SY**stem for **CU**stoms **DA**ta) with 80 countries using the system today. Up to its latest version (ASYCUDA World), this system was closed and did not allow customs authorities to develop efficient risk management applications. ASYCUDA's risk 'management' module was forced on Customs and depended on the option of being able to apply and combine simple selection criteria (lists of importers, origins, etc.). The new version of ASYCUDA is more open and allows the development of country-specific applications. Côte d'Ivoire, Mali and Senegal (the latter country uses its own computer system for customs clearance, GAINDE) have therefore undertaken to develop their own risk management applications, notably with the technical assistance of the International Monetary Fund's (IMF) West Africa Regional Technical Assistance Centre (West AFRITAC).

The aim of this article is to present and compare simple statistical techniques that contribute to the modernisation of customs administration systems by enabling efficient targeting of the declarations to be inspected. These techniques can be developed by most developing countries' customs authorities, which are increasingly recruiting officers with the necessary statistics and mathematics skills.

From descriptive statistics to decision-making statistics

Whatever the sector of activity, statistical targeting techniques use available data. In Customs, data come from declarations, from the results of first- and second-line inspections, and from private inspection companies via the verification certificates that they issue.

The information obtained from these various sources makes up the customs information system which, among other things, allows a risk management system to be constructed and declarations to be directed to the different customs clearance channels. Unfortunately, customs authorities only exploit a small part of the wealth of information available that flows through the customs clearance process and their control activities.

Indeed, information processing is essentially qualitative in terms of the approach to selectivity. The selectivity criteria used are often few in numbers and the analysis for each criterion is most often dual (whether or not it is listed). Thus, if origin X is in the list of risk sources, as soon as a declaration gives that origin, an intrusive examination will be triggered – even if the declaration is made by a known and serious importer. There is thus no gradation in risk perception and this reduces targeting performance. This leads to high rates of intrusive inspections in exchange for low rates of reported infractions; that is, a relatively inefficient risk management system. This low targeting efficiency is determined by a defective statistical analysis of risk that does not leverage the available customs information in an optimal manner.

Descriptive statistics: data mining

To succeed in accurately targeting declarations that present a risk of infraction, it is necessary to carry out prior work on data analysis, on descriptive statistics. This work requires Customs to identify the characteristics of declarations that, in a preceding period (for example, over the previous twelve months) has resulted in an infraction, and then deducing the 'statistical regularities' in those infractions. For this reason, all available information is used, that is, the contents of verification certificates, detailed declarations, and the results of inspections during a reference period. These statistical regularities enable risk profiles to be established.

Indeed, while the information is essentially qualitative in its use of selectivity criteria, statistical analysis makes it possible to establish a 'quantitative' risk scale. Let us take the example of importers: to measure the 'quality' of importers, the frequency of infractions is calculated for each importer (this is the ratio between the number of declarations made by an importer involved in a customs infraction and the total number of declarations made by that importer during the period in question). Thus, importers are rated on a scale from 0 to 1 (or 0 to 100), where 0 is for importers that represent no risk and 1 for importers that represent a high risk. This type of calculation can be done for all potential risk criteria: origin, HS position, billing currency, freight agents, and so on. These calculations enable the establishment of risk profiles for each criterion (see Figure 1).

Decision-making statistics: referring declarations to a customs clearance channel

Next, we need to combine these risk profiles to facilitate the right decision with regard to referring the declaration to a particular customs clearance channel. The combination of criteria may be simple (statistical average) or more elaborate (econometric analysis). In both cases, the objective is to assign a score to each new declaration, obtained by combining the frequencies of infraction for the different criteria (risk profiles). At best, this score should reflect risk of infraction (or even the probability of an infraction occurring). Referral to one of the customs clearance channels is based on the score and thresholds previously determined through statistical analysis (see Figure 1).

With the simplest system, the score for the declaration is obtained by applying a simple or weighted average of infraction frequency for the different criteria, or by taking only the value of the highest frequency from among the criteria used (other combinations can be thought of). Prior to this, the most significant criteria will have been determined *ad hoc* by customs officers responsible for control activities. The most common and significant criteria are importer, freight agents, HS position and origin.

A more elaborate system uses statistical distribution properties to effectively combine customs information. Econometric models (combining statistical and mathematical approaches) enable (1) the determination of risk criteria relevant in accounting for an infraction; and (2) the calculation of the probability of infraction for each new declaration introduced in the customs clearance system. This probability is the calculated score for the declaration. For this purpose, it is first necessary to estimate the following econometric equation on the background history of the declarations:

$$\Pr(Infraction_{ij} = 1) = \alpha + \beta_1 fq\_\ crit\grave{e}re1_{ij} + \beta_2 fq\_\ crit\grave{e}re2 + \ldots\ldots_{ij} + \beta_N fq\_\ crit\grave{e}reN_{ij} + \varepsilon_{ij}$$

where Pr is probability; Infraction $_{ij}$ the binary 0/1 variable for declaration i, product j (1 if infraction, 0 if no infraction for the declaration j and for product i) $fq\__{ij}$, the frequency of customs infractions for each criterion of risk associated with declaration i and product j, ε, error term (which is not explained by the criteria used in the equation) and α and β as the parameters of the equation to be estimated.

The use of background history involves looking over all the declarations for a reference period, giving a mark of '1' to those that have been found in infraction and '0' to those that have not. The binary variable 0/1 is thus constructed ('explained' or 'dependent' variable). This variable is then 'explained' by risk criteria ('explanatory' or 'independent' variables), the values of which are continuous between 0 and 1.

The estimate can be drawn from a linear probability model, a PROBIT model or a LOGIT model. The last two of these models are the most appropriate for estimating a model with a binary explained variable. Indeed, some stochastic assumptions are violated in linear regression. The error term occurs through heteroskedastic construction and does not follow normal distribution. Furthermore, the predicted value cannot be interpreted as a probability of infraction since it does not belong to the interval [0, 1]. If the LOGIT and PROBIT models are 'in theory' the most appropriate, then the end goal is to find a model capable of better targeting those declarations that present real risk of infraction. The three models can therefore be tested and the one presenting the best results should be accepted.

From theory to practice: results from some empirical tests

The tests presented use a database created by Senegalese customs authorities. Indeed, in 2011, the Senegalese customs authorities propose incorporation of a risk management module into their customs clearance system, GAINDE 2010[1]. The confidentiality of customs data and the effectiveness of the system itself preclude the specific presentation of the criteria used, but this does not impede comparison of the results according to the different methods proposed.

The database used covers twelve months. Data comes from detailed declarations and monthly statements of customs infractions for the two main offices in Dakar. Verifications certified by the inspection company are not taken into account. Risk profiles (based on frequency of infraction) were calculated for six different criteria: importer, freight agents, HS position, origin, provenance, and customs regime. Only declarations from operators with an identification number were taken into account in these tests.

Six different scoring calculations are done and their performance is compared for the purposes of targeting declarations. The effectiveness of targeting is measured by comparing, for each declaration from the period in question, the occurrence of an infraction with the calculated score. If the calculated score is high, –that is, if the estimated risk of infraction is high, the declaration should be subject to an infraction (binary variable = 1). If this is the case, the system enables the targeting of risky declarations. On the other hand, if the calculated score is high and the declaration was not subject to an infraction (binary variable = 0), the calculated score does not enable effective targeting. Similarly, if the calculated score is low, the declaration should not be subject to an infraction (binary variable = 0). If this is the case, the system enables good targeting. If the opposite is the case, it does not enable good targeting. This method of measuring effectiveness is applied regardless of the score calculation method.

Simple methods for score calculation

Among the six criteria adopted *a priori*, three were identified as very important by the Senegalese customs authorities. Thus, for all the declarations stored in the database, the score of each declaration was calculated based on the risk profiles for these three criteria in accordance with three different methods: (1) a simple average of the frequency of infraction; (2) a weighted average of the frequency of infraction, with 0.5, 0.3 and 0.2 weighting; and (3) by accepting only the maximum value for the frequency of infraction for the three criteria adopted.

To facilitate the analysis of the results, declarations are grouped into ranges of scores (those that have a calculated score of between 0 and 0.01, then between 0.01 and 0.02, and so on). The results can be seen in the following tables. The choice of intervals is important because it will determine the thresholds that refer declarations to the various customs clearance channels. Ten intervals have been chosen here to make it easier to read the tables.

Figure 1: Risk Management System: an illustrative example
(Score of declaration = result from a probability model; all data shown here are fictitious)

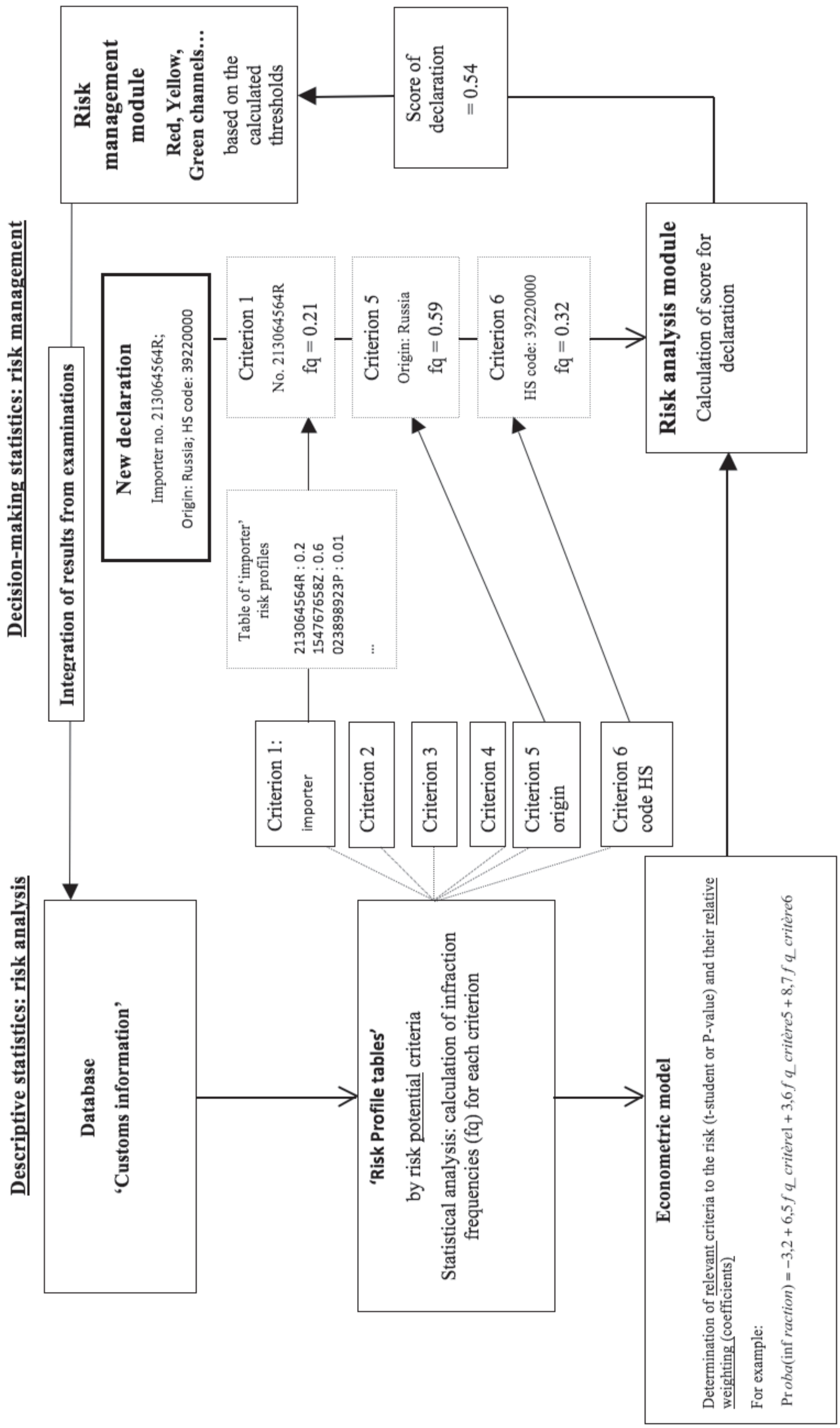

Table 1: Effectiveness of targeting – simple average (1)

Score interval	Number of declarations for the interval	Number of accumulated declarations	Accumulated declarations (%)	Number of declarations with infraction	Number of accumulated declarations with infraction	Rate of infraction by interval	Accumulated declarations with infraction (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
[0.5 : 1]	0	0	-	0	0	-	0.0
[0.1 : 0.5]	825	825	0.8	351	351	42.55	31.8
[0.07 : 0.1]	503	1328	1.3	112	463	22.27	41.9
[0.06 : 0.07]	470	1798	1.7	61	524	12.98	47.4
[0.05 : 0.06]	618	2416	2.3	63	587	10.19	53.1
[0.04 : 0.05]	1014	3430	3.3	130	717	12.82	64.9
[0.03 : 0.04]	2027	5457	5.2	124	841	6.12	76.1
[0.02 : 0.03]	4895	10352	9.9	142	983	2.90	89.0
[0.01 : 0.02]	20292	30644	29.3	81	1064	0.40	96.3
[0 : 0.01]	74053	104697	100.0	41	1105	0.06	100.0
Total	104697			1105		1.06	

Table 1 is read as follows: Column 1 shows the selected intervals. Column 2 shows the number of declarations with a calculated score within the range: 20,292 declarations have a calculated score of between 0.01 and 0.02. Column 3 shows the cumulative number of declarations: there are 30,644 declarations with scores between 0.01 and 1. Column 4 shows these cumulative declarations as percentages: the declarations that have a calculated score of between 0.01 and 1 (that is, greater than 0.01) represent 29.3% of all declarations. Column 5 shows the number of declarations showing an infraction by interval: among the 20,292 declarations with a calculated score of between 0.01 and 0.02, 81 have actually been subject to an infraction. Column 6 shows the cumulative number of declarations that have had an infraction: there are 1,105 declarations that involved an infraction – an infraction rate of 1.06% (column 7). Column 8 shows the cumulative number of declarations showing infractions: 96.3% of declarations showing infractions have a calculated score of between 0.01 and 1 (that is, above 0.01).

Table 2: Effectiveness of targeting – weighted average (2)

Score interval	Number of declarations for the interval	Number of accumulated declarations	Accumulated declarations (%)	Number of declarations with infraction	Number of accumulated declarations with infraction	Rate of infraction by interval	Accumulated declarations with infraction (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
[0.5 : 1]	98	98	0.1	94	94	95.92	8.5
[0.1 : 0.5]	1165	1263	1.2	348	442	29.87	40.0
[0.07 : 0.1]	954	2217	2.1	121	563	12.68	51.0
[0.06 : 0.07]	448	2665	2.5	56	619	12.50	56.0
[0.05 : 0.06]	788	3453	3.3	98	717	12.44	64.9
[0.04 : 0.05]	1152	4605	4.4	85	802	7.38	72.6
[0.03 : 0.04]	2427	7032	6.7	109	911	4.49	82.4
[0.02 : 0.03]	2645	9677	9.2	83	994	3.14	90.0
[0.01 : 0.02]	11897	21574	20.6	73	1067	0.61	96.6
[0 : 0.01]	83123	104697	100.0	38	1105	0.05	100.0
Total	104697			1105		1.06	

How to analyse these results. By targeting (inspecting) all declarations that have a calculated score above 0.02, that is, 9.9% of declarations, the system captures 89% of declarations that have been subject to infraction. If the threshold is lowered to 0.01, this rises to 96.3% of declarations that have been subject to infraction, captured by inspecting only 29.3% of declarations.

How to use these results. If customs authorities set a 0.01 threshold for intrusive examinations, any new declaration recorded in the customs clearance system that shows a calculated score higher than 0.01 will be referred to an intrusive examination channel; that is, approximately 30% of declarations. The threshold can be adjusted according to the customs authorities' objectives.

Score calculation based on weighted average improves targeting effectiveness. By targeting all declarations with a score higher than 0.01 (that is, 20.6% of declarations), the system captures 96.6% of declarations with infractions, that is, an inspection rate much lower than is currently practised in many developing countries.

Table 3: Effectiveness of targeting – maximum value (3)

Score interval	**Number of declarations for the interval**	**Number of accumulated declarations**	**Accumulated declarations (%)**	**Number of declarations with infraction**	**Number of accumulated declarations with infraction**	**Rate of infraction by interval**	**Accumulated declarations with infraction (%)**
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
[0.5 : 1]	143	143	0.1	126	126	88.11	11.4
[0.1 : 0.5]	2954	3097	3.0	510	636	17.26	57.6
[0.07 : 0.1]	1926	5023	4.8	136	772	7.06	69.9
[0.06 : 0.07]	956	5979	5.7	41	813	4.29	73.6
[0.05 : 0.06]	2569	8548	8.2	68	881	2.65	79.7
[0.04 : 0.05]	3172	11720	11.2	56	937	1.77	84.8
[0.03 : 0.04]	7691	19411	18.5	60	997	0.78	90.2
[0.02 : 0.03]	23027	42438	40.5	41	1038	0.18	93.9
[0.01 : 0.02]	49402	91840	87.7	61	1099	0.12	99.5
[0 : 0.01]	12857	104697	100.0	6	1105	0.05	100.0
Total	104697			1105		1.06	

Calculating the score according to maximum value is the least effective, since 18.5% of declarations need to be targeted in order to capture 90.2% of declarations with infractions.

Econometric methods for score calculation

Three estimations were used: (4) estimation by a linear probability model; (5) estimation using a LOGIT model which uses the logistical distribution, and (6) estimation using a PROBIT model, based on normal distribution.

The linear probability model

The equation is estimated using the ordinary least squares method, corrected by heteroskedasticity. The explained variable is the binary (0/1) 'infraction' variable. The explanatory variables are the risk criteria. Four of these variables show a coefficient that is significantly different from zero. The adjusted R^2 is 0.23. The failure to respect the residual normality hypothesis means the usual econometric tests cannot be run. Estimating the variable coefficients in the equation enables calculation of the score for each declaration and conduct of the targeting effectiveness test.

Table 4: Effectiveness of targeting – Linear Probability (4)

Score interval	Number of declarations for the interval	Number of accumulated declarations	Accumulated declarations (%)	Number of declarations with infraction	Number of accumulated declarations with infraction	Rate of infraction by interval	Accumulated declarations with infraction (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
[0.5 : 1]	147	147	0.1	131	131	89.12	11.9
[0.1 : 0.5]	2506	2653	2.5	489	620	19.51	56.1
[0.07 : 0.1]	1455	4108	3.9	157	777	10.79	70.3
[0.06 : 0.07]	957	5065	4.8	48	825	5.02	74.7
[0.05 : 0.06]	1234	6299	6.0	55	880	4.46	79.6
[0.04 : 0.05]	1407	7706	7.4	61	941	4.34	85.2
[0.03 : 0.04]	1500	9206	8.8	39	980	2.60	88.7
[0.02 : 0.03]	2287	11493	11.0	37	1017	1.62	92.0
[0.01 : 0.02]	7171	18664	17.8	43	1060	0.60	95.9
[0 : 0.01]	86033	104697	100.0	45	1105	0.05	100.0
Total	104697			1105		1.06	

Although econometric estimation is biased by construction, its result in terms of targeting is good and slightly better than that of the simple methods. By targeting all declarations with a calculated score higher than 0.01, that is, 17.8% of declarations, the system captures 95.9% of declarations with infractions.

The PROBIT and LOGIT models

These two nonlinear models enable an estimate of the probability that a declaration may contain an infraction. The variables used are the same as for the linear probability model. The estimates are adjusted for the heteroskedasticity problem.

The estimate of the equation based on the LOGIT model has a Pseudo-R^2 of 0.32 and that based on the PROBIT model results in a Pseudo R^2 of 0.36. The six explanatory variables are significant. Both estimates enable the calculation of the probability that a declaration may contain infractions.

Table 5: Effectiveness of targeting – Probability calculated with a LOGIT model (5)

Score interval	Number of declarations for the interval	Number of accumulated declarations	Accumulated declarations (%)	Number of declarations with infraction	Number of accumulated declarations with infraction	Rate of infraction by interval	Accumulated declarations with infraction (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
[0.5 : 1]	414	414	0.4	251	251	60.63	22.7
[0.1 : 0.5]	736	1150	1.1	173	424	23.51	38.4
[0.07 : 0.1]	306	1456	1.4	60	484	19.61	43.8
[0.06 : 0.07]	148	1604	1.5	18	502	12.16	45.4
[0.05 : 0.06]	274	1878	1.8	33	535	12.04	48.4
[0.04 : 0.05]	335	2213	2.1	18	553	5.37	50.0
[0.03 : 0.04]	701	2914	2.8	65	618	9.27	55.9
[0.02 : 0.03]	1799	4713	4.5	117	735	6.50	66.5
[0.01 : 0.02]	7702	12415	11.9	178	913	2.31	82.6
[0 : 0.01]	92282	104697	100.0	192	1105	0.21	100.0
Total	104697			1105		1.06	

Table 6: Effectiveness of targeting – Probability calculated witha PROBIT model (6)

Score interval	Number of declarations for the interval	Number of accumulated declarations	Accumulated declarations (%)	Number of declarations with infraction	Number of accumulated declarations with infraction	Rate of infraction by interval	Accumulated declarations with infraction (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
[0.5 : 1]	405	405	0.4	245	245	60.49	22.2
[0.1 : 0.5]	889	1294	1.2	215	460	24.18	41.6
[0.07 : 0.1]	396	1690	1.6	52	512	13.13	46.3
[0.06 : 0.07]	221	1911	1.8	32	544	14.48	49.2
[0.05 : 0.06]	255	2166	2.1	18	562	7.06	50.9
[0.04 : 0.05]	341	2507	2.4	35	597	10.26	54.0
[0.03 : 0.04]	709	3216	3.1	61	658	8.60	59.5
[0.02 : 0.03]	1988	5204	5.0	115	773	5.78	70.0
[0.01 : 0.02]	5618	10822	10.3	160	933	2.85	84.4
[0 : 0.01]	93875	104697	100.0	172	1105	0.18	100.0
Total	104697					1.06	

Although the method is statistically more rigorous, estimates on the basis of a LOGIT or PROBIT model do not enable improvement of targeting effectiveness. Indeed, by targeting declarations that have a calculated score above 0.01 (that is, between 10% and 12% of declarations, depending on the model), the system captures only 82-84% of declarations containing infractions depending on the model, that is, a rate lower than that of other calculation methods.

Why do we get these results? The quality of the database is certainly the most plausible explanation. Indeed, declarations with infractions are rare (about 1% of the declarations in this database), which the LOGIT and PROBIT models find hard to accommodate. The reality is certainly different.

Good targeting is a factor in improving customs information systems and, hence, the database that feeds the system. Indeed, by controlling less and in a different manner (second-line controls that substitute first-line controls), services are made to control better. Over time, database quality improvement should restore advantage to the PROBIT and LOGIT models which are especially well-suited to scoring.

Some lessons for customs authorities of developing countries

Streamlining customs controls is one of the keys to modernising customs administration in developing countries. Using statistical techniques can substantially improve the efficiency of targeting declarations to be inspected. The 'statistical techniques' aspect is no obstacle to customs authorities developing an effective risk management system. The simple methods proposed are accessible to all staff trained to a masters degree level in economics or statistics.

The proposed tests show that statistical techniques allow effective targeting of declarations. They have a good ability to predict and detect declarations containing infractions.

Thus, a developing country's customs authorities can build, stage by stage, a risk management system at the pace at which it acquires staff skills and practice, while serving as the driving force behind the modernisation of the first stage. A period of two to three years is sufficient to develop such a system in three main stages.

The first stage is to establish risk profiles by criterion and simply combine them (in a weighted average, for example). This stage is already possible in most developing countries' customs authorities; countries such as Côte d'Ivoire, Senegal and Mali have managed this fast. This system can effectively replace the current, rather inefficient systems of selectivity, without risk to either tax revenues or the country's security.

Since the database is fed by more reliable data, the second stage is to apply econometric scoring techniques – usually more effective than averaging – because they are based on statistical distributions. Binomial models are the easiest to implement. The information analysed on the background history of declarations is binary: has the declaration been subject to an infraction – yes or no? The information returned is binary too: does the new declaration present an increased risk of information – yes or no? The model says nothing about the nature of the infraction. The second stage comes into play when the customs information system is not sufficiently informed about the nature of the infractions confirmed. The information revealed is the presumption of infraction, whereby the control officers must define the nature of the infraction.

The third step entails setting up a comprehensive and accurate customs information system on recorded infractions. These multinomial models are then used to provide information about the nature of the infraction that is being considered.

These statistical methods are just one component of the risk management system. Random controls, selectivity on new fraud forms detected by the intelligence services, selectivity from the moment one characteristic of the declaration is not entered in the database, are complementary to the statistical analysis.

The combination of all these elements creates an effective risk management system that helps reduce the number of intrusive inspections without risk to the country. Reducing the number of first-line inspections makes it possible to improve the inspection performed as well as to develop *a posteriori* inspection. Developing *a posteriori* inspections should be an opportunity to bring together Customs and tax authorities, thereby contributing to greater efficiency in total government revenue. Trade facilitation and improving revenue collection are therefore perfectly compatible.

External technical assistance regarding risk management systems enables developing countries to invest more quickly and solidly in modernising their customs authorities. This external technical assistance, however, is beneficial only if the customs authorities adopt an up-to-date management of their human resources: staff in charge of these technical matters should be recruited on the basis of well-defined job descriptions and personnel assigned to risk management services should be appointed for the long term.

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Endnote

1 'GAINDE' is the French acronym for Automated Management of Customs and Economic Information.

Bertrand Laporte

Professor Bertrand Laporte is a member of CERDI (Centre for Study and Research into International Development) and 'maître de conferences' at the Université d'Auvergne. He is co-director of the Public Finance in Developing and Transition Countries master's course, and has spent almost 20 years working on international trade, tax and customs administration issues. He is a member of the panel of experts of the International Monetary Fund (IMF) Fiscal Affairs Department and works for a number of international institutions.