Risk Management in Border Inspection*

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Abstract

As part of their commitments under the World Trade Organization's *Agreement on Trade Facilitation*, many developing countries are set to adopt risk management, a strategy for selecting import shipments for inspection. In this paper we formalize key enforcement issues related to risk management. We argue that the complexities of international trade oversight mean that inspecting agencies lack certainty about the conditional probability that a given shipment will not comply with import regulations. *Ambiguity* of this sort is likely to be especially important in developing countries that lack the sophisticated information technology (IT) used in advanced risk management systems. We formalize a role for ambiguity in a theoretical model of border inspection. We provide evidence suggesting that ambiguity affects inspection rates. Finally, we calibrate the model and shock the ambiguity parameters to illustrate the consequences of an IT-driven improvement in risk management capabilities for equilibrium rates of search and compliance.

Keywords: Trade Facilitation; Risk Management; Border Inspection; Ambiguity Aversion; Choquet Expected Utility.

JEL classification: D73; D81; F18.

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1 Introduction

The World Trade Organization's *Agreement on Trade Facilitation* (TFA) contains a broad body of reform measures that are meant to expedite the movement of international goods trade. A key reform in this package is risk management, a strategy for selecting imported goods shipments for inspection. Effective risk management focuses inspection resources on shipments that are at high-risk for non-compliance with import regulations, while reducing the inspection burden on low-risk shipments. Reforms of this kind typically include the adoption of sophisticated information technology (IT) that is used to communicate information about the shipment, assess risk, and store inspection results for the purposes of ongoing improvements in risk assessment. Implementation of modern risk management methods requires inspecting agencies to make multi-year investments in IT, and in retraining their staff. A better understanding of the nature and size of the benefits from reform can inform the decision of when and where to implement it.

In this paper we offer a theoretical framework for understanding the benefits that flow from risk management reforms, and isolate a structural channel through which IT generates these benefits. Agencies conducting oversight over import shipments must consider a wide range of potential harms related to thousands of different products sourced from dozens of countries and involving countless trading firms.[1] We argue that these circumstances imply an important role for *ambiguity*, a theoretical concept that is absent in standard economic models of policing. Ambiguity in this context represents uncertainty about the probability that a shipment complies with import regulations. We argue that a key contribution of modern IT in this setting is to reduce ambiguity; the information storage and analytical tools that modern systems provide allow the agency to better use information from the import declaration to predict the conditional probability that a given shipment is non-compliant. Reductions in ambiguity allow better targeting of inspection resources, thereby allowing key

[1]The harms that we consider are broad, including tariff evasion, violation of food safety or other product standards, invasive species and other environmental harms, such as plant and animal health. Harm associated with smuggled contraband can be mapped onto our model, but perhaps not as cleanly as other types of non-compliance with import regulations.

enforcement goals to be reached, even as the overall inspection burden is reduced.

Our focus on ambiguity is motivated by discussions with operational experts in trade logistics, but we also offer some empirical evidence on the role of ambiguity in the inspection decision using data from Serbian Customs.[2] Ambiguity is not directly observable in the data, but we are able to show that the lagged number of shipments that Serbian customs observed in a given product-country-firm combination correlates negatively with the conditional probability of inspection in the current year. This suggests that when the inspecting agency has greater experience with a given type of shipment, they search that type less frequently. To better understand the type and size of benefits that flow from reform, we calibrate a numerical version of the model to statistics from the Serbian data, and consider the consequences of removing risk management capabilities that are already in place there.

Our framework for incorporating ambiguity in the inspection decision is a form of Choquet Expected Utility (CEU) theory, as described in Schmeidler (1989). In CEU theory, inspectors' beliefs about probabilities of non-compliance are represented as normalized and monotone set functions known as *capacities*. Importantly, capacities allow the model to separate inspectors' beliefs from the conditional probability that a good is non-compliant (in contrast to standard assumptions about beliefs in the expected utility framework). We adopt a particular form of capacities: the non-extreme-outcome additive (neo-additive) capacity described in Chateauneuf, Eichberger and Grant (2007). Our contribution is to illustrate the benefits of the framework for understanding the challenges facing border inspection agencies, and the role IT plays in reform. Our framework may also be useful for understanding other probabilistic approaches to law enforcement.[3]

A closely related literature studies police searches of civilians for contraband, and in that

[2]We use data from Serbian Customs because it provides information on inspection activity and we have it available to us. Risk management involving modern IT is already in place in Serbian Customs, which is one reason that high quality data is available. We suspect that ambiguity is less important for Serbian Customs than for customs agencies in countries with less developed systems or for non-customs agencies that lack similar capabilities with IT.

[3]Other applications of the CEU framework include Teitelbaum (2007), which examines a unilateral accident model with ambiguity and constructs an efficient ambiguity-adjusted liability rule. In an audit context, Bigus (2012) models unilateral auditor liability under ambiguity aversion. Both of these papers have a different focus than ours.

context formalizes conditions that would constitute racial or other kinds of discrimination in police search behavior. Knowles *et al.* (2001) and Persico (2002) use an expected utility framework to formalize the decision to search an individual and/or his property (e.g., automobile).[4] An implication of expected utility theory is that the police officer is assumed to know, with certainty, the probability – conditional on an observable characteristic or characteristics such as the civilian's race – that a search of an individual or her automobile will find contraband. Our primary departure from this literature is formalizing a role for ambiguity about the underlying probability distribution. It is likely that ambiguity is more important in the international trade context given (a) the large number of characteristics of an import shipment, and (b) the fact that many import shipments have bundles of characteristics that are only rarely observed together.[5] We also focus on overall search intensities and compliance – rather than discrimination with respect to characteristics – since the equal protection issues important for police searches are less relevant in the context we study.[6] In the border management context, risk management generates very different search intensities for shipments with different characteristics (e.g., product type and/or country of origin), an outcome that the police search literature would likely attribute to bias.

The operational literature on risk management in border inspection is typically less formal than what we offer here. Widdowson and Holloway (2011) describe risk management using a heuristic framework that can be understood in terms of expected utility theory.[7] Our conversations about best practices with World Bank operational experts in developing country border management suggest an important role for ambiguity. For example, one

[4]A user-friendly introduction to those papers can be found in Persico and Todd (2008), which also discusses some caveats to the theory. Another related paper is Eeckhout *et al.* (2010), which shows that random crackdowns can be an optimal policing strategy. Lazear (2006)'s paper on high-stakes testing in education is also relevant for its potential applicability to crime.

[5]Armenter and Koren (2014) show that, even in U.S. data, trade data are extremely sparse. The most common number of shipments for a product-country-firm observation is one.

[6]Furthermore, while we focus on the planner's problem (i.e., the inspecting agency), both Knowles *et al.* (2001) and Persico (2002) look at the optimal behavior of a single officer (among many) to determine if there is any discrimination in equilibrium. This distinction is important since while deciding on search intensity, the agency takes into account the effect of its decision on the overall compliance rate, while the individual officer does not.

[7]For example, Table 6.1 on p.104 in Widdowson and Holloway (2011) presents a risk matrix with 'likelihood' along one axis and 'consequence' along the other.

practice described in these discussions is to conduct a full physical inspection for each new combination of product, origin country, and firms involved in import transactions.[8] This strategy represents an effort to reduce ambiguity.

A small empirical literature has studied the operation of risk management and/or the effects of reform episodes related to the oversight of international goods trade. Martincus *et al.* (2015) show that inspections impede exporting in a study of the risk management system that governs Uruguayan exports. Fernandes *et al.* (*forthcoming*) conduct an evaluation of the effects of reduced inspections of import shipments by Albanian customs during a period of substantial reform. Fernandes *et al.* (2017) evaluate preliminary steps towards a reform undertaken by the Food and Veterinary Agency of North Macedonia. Cariolle *et al.* (2019) and Chalendard *et al.* (2019) show how external information on trade flows can be used to forecast tariff evasion in Gabon and Madagascar, respectively.

In our paper we apply tools from decision theory to understand the contribution of IT to risk management reforms associated with oversight of shipments of imported goods. We argue that the rarity of many import shipments makes untenable a presumption that inspecting agencies are fully informed about conditional probabilities of non-compliance. But we also argue that a key contribution of modern IT systems is to reduce the ambiguity present in the border environment. We offer empirical evidence showing that the conditional correlation between the number of lagged import shipments with a given bundle of characteristics and the probability that a shipment with those characteristics is inspected is negative. Finally, we calibrate the model in order to illustrate quantitative relationships between ambiguity, search intensities and firms' compliance with import regulations.

The rest of the paper is organized as follows. Section 2 briefly describes the operation of modern risk management systems as they apply to oversight of imported goods shipments. Section 3 develops the theoretical framework incorporating ambiguity. Section 4 describes the equilibrium, and derives comparative static predictions of the model. Section 5 offers empirical evidence on inspection behavior from Serbia. Section 6 calibrates a numerical

[8] We thank Lazar Ristic of the World Bank for providing us with this example.

version of the model and conducts counterfactual analysis. Section 7 concludes. The general framework describing the neo-additive capacity and the Choquet integral is relegated to the appendix.

2 Risk-based methods in border management

Risk-based approaches to inspection have become a central component of border management in developed countries. Risk management is considered to be a 'best practice' strategy in the oversight of international goods trade. It appears in international agreements such as the World Customs Organization's *Revised Kyoto Convention* and the TFA. In many countries the customs agency already employs some form of risk management, though improvements are often necessary. A more difficult step is the adoption of risk-based inspection methods in so-called 'technical' agencies, those responsible for ensuring compliance with regulations concerning food safety, human and animal health, and the environment.[9]

In this section we sketch the outlines of a reform episode that implements modern risk management strategies that include advanced IT. Prior to a reform, analysis of available data on inspections often finds very high rates of inspection, paired with relatively low rates of failed inspections.[10] These outcomes jointly suggest that not only are there too many inspections, but also that they are poorly targeted. The absence of coordinated risk assessment may mean that one source of poor targeting is heterogeneous priors – across individual inspectors or across inspection teams located at different control points – about conditional probabilities of non-compliance. Risk management reforms typically centralize the task of risk assessment, improve the quality of data available for making those assessments, and improve the system's capacity to forecast probabilities of non-compliance.

In the initial stages of a reform, a committee of centrally-located experts (often aided

[9]Technical agencies oversee the movement of fewer shipments than the customs agency, but also conduct more intrusive inspections – including lab tests, for example. They are also usually less well-resourced than the customs agency, and subsequently less likely to have adopted modern risk management methods involving IT. Fernandes *et al.* (2017) study a partial reform in a technical agency.

[10]See descriptions of pre-reform environments in Fernandes *et al.* (2017), in particular, and in Fernandes *et al.* (*forthcoming*).

by foreign expertise) define the range of potential harms that inspections are meant to avoid, and associate likely harms with non-compliant imports of particular products. The central committee also gathers available information from past inspections to understand the frequency and types of non-compliance, and the distribution of non-compliance across a wide range of shipment characteristics. The information on harms and on non-compliant imports is combined to inform a national strategy that generates different *a priori* inspection probabilities across shipments based on the outcome of a rigorous risk assessment process.

Another central component of reform is the adoption of advanced IT systems.[11] These systems facilitate risk management in a number of ways. First, they allow reliable electronic storage and fast recall of detailed information on past inspection activity and outcomes. Second, IT systems combine detailed information from the import declaration on the shipment's characteristics with the parameters set by the central committee to make a rapid determination of the risk posed by each shipment. Third, IT can improve compliance forecasts for less-frequently-observed shipments with statistical analysis of more frequent shipments that share important characteristics with the infrequent shipments. Finally, by facilitating rapid communication – including guidance from the center on news of emerging hazards, or communication to the center of changes in non-compliance rates on the ground – IT helps inspecting agencies to rapidly update the conditional priors that guide the inspection decision in times when compliance rates are changing.

Once it is operational, the risk management system operates as follows. Information from the central committee parameterizes a risk model using information on the severity of harm from non-compliant imports of a given product and the past evidence of the likelihood of non-compliance of shipments with different characteristics. When a shipment arrives at a port, border crossing or other inspection location, the trading firm files an import declaration associated with that shipment. The import declaration contains a large number of fields – including country of origin, a detailed product classification, and a complete listing of firms

[11] A common IT system used in developing country customs agencies is ASYCUDA, a low-cost, off-the-shelf risk management system developed by the United Nations Committee for Trade and Development. Even when the purchase price of IT systems is low, agencies must spend considerable resources on retraining personnel to use such systems.

involved in the transaction and in the logistics supply chain. The risk management system applies predetermined weights to data in each of these fields, as well as information on the scale of possible harms associated with a non-compliant shipment of this type, in order to generate a 'risk score' which is used to determine whether or not the shipment is inspected. Inspectors conduct the search when the system recommends it.[12] The outcome of the search is recorded electronically, and communicated to the central committee for the purposes of updating the risk model.

2.1 Effects of information technology on system performance

In our view the four contributions of IT listed above can be understood as effectively reducing the ambiguity surrounding the inspecting agency's *ex ante* expectation of the probability that a shipment with given observable characteristics will not be compliant with import regulations. Improved capabilities of storage and recall allow the history of a shipment with given characteristics to better inform the agency's forecast of non-compliance for shipments that share the same specific bundle of characteristics. Information from more frequent shipments can be used to estimate the marginal contribution of specific shipment characteristics to compliance, thereby improving the agency's forecast of compliance probabilities for less frequently-observed shipments with similar characteristics. The combination of nationally-collected information on relationships between shipment characteristics and non-compliance, together with a common well-defined understanding of possible harms, reduces heterogeneity in the inspection decision that might otherwise exist across individual inspectors or inspecting offices. The IT systems' ability to facilitate the rapid flow of accurate information allows rapid updating of *ex ante* probabilities as new information emerges. All these features of IT act to compress realized variation in the conditional forecast of the probability of non-compliance. This motivates our analysis of reduced ambiguity in the theoretical model.

[12] Inspectors usually have the capacity to intensify the search based on their initial findings. In some contexts they may also have autonomy to initiate a search without guidance from the system, though this would be rare when compared to searches initiated because of guidance from the IT system.

3 Model

In this section we present a stylized model. Our approach to the theory is meant to illustrate the flexibility of the framework for application to different settings. In the numerical simulation in section 6, we choose a setting, functional forms and parameters that illustrate the operation of the model in a portion of the parameter space that is relevant to reform.

In the model shipments of traded goods arrive to the country's border, and there are risks associated with the goods in regard to health, safety and environment (from now on HSE). To control these risks, the border inspection agency searches shipments of goods from time to time. We assume that each shipment is associated with a unique good and a unique firm such that searching a shipment means searching the firm importing that shipment. There is an upper bound on the maximum number of searches the agency can perform, which is given by $\overline{S}$.[13] When a search is performed, we assume that a non-compliant good is identified with probability 1. There is a continuum of goods and each good can be categorized with respect to its observed characteristics, such as country of origin, transportation method, etc. For expositional purposes, assume that we have two mutually exclusive characteristics, say A and B.[14,15] Some goods are in category A, some are in category B. As a result, we have a total of 2 groups, say 1 and 2 with measures N_1 and N_2, respectively. Throughout, index $l \in \{1, 2\}$ will denote the group.

There is a threshold level of compliance that must be satisfied. If a good is searched and found not to satisfy this compliance threshold, the good cannot enter the country and the importer incurs a loss of $\$L > 0$.[16] We assume that each good can satisfy this threshold by incurring some cost that depends on the good's particulars. Let $c(y)$ represent the cost

[13] One possible way to justify this assumption is to consider a case where a budget for search is limited. Alternatively, it can be due to a time constraint.

[14] There are different ways to interpret these characteristics. For example, A may represent shipments from developing countries whereas B may represent shipments from developed countries. Alternatively, A may represent shipments of new importers while B may represent shipments of seasoned importers.

[15] It is straightforward to generalize the model to any number of mutually exclusive characteristics.

[16] This loss can represent either the loss incurred by not entering the country or a fine charged for failing to comply. It can potentially vary from one good to another. We simply assume it to be constant since our results continue to hold as long as the deterrence is not perfect.

required for a good with particulars y. We assume that $c(.)$ is invertible and $c' > 0$ and y is a realization of a random variable Y_l with the cdf of F_l and pdf of f_l for $l \in \{1, 2\}$. Thus, we allow the distribution of goods' particulars to differ across groups. Moreover, both Y_l's are non-negative, and their supports include zero. A good's particular, hence compliance cost, is unobservable to the border inspection agency. On the other hand, given the good's characteristic the inspecting agency can observe the group to which the good belongs.[17]

Denote S_l the measure of searches of shipments in group l. Denote with $s_l = \frac{S_l}{N_l}$ the search intensity in group l. s_l represents the probability that a random shipment in group l is searched. As a result, we must have

$$N_1 s_1 + N_2 s_2 = \overline{S}.$$

For a given search intensity, importers of each good decide whether to incur the cost to comply or not. They will comply *if and only if*

$$c(y) < s_l L, \text{ which is}$$
$$y < c^{-1}(s_l L).$$

The function $c^{-1}(s_l L)$ represents the expected benefit of compliance to the HSE standards when the search intensity is s_l and the loss of not satisfying the compliance standard is L. Hence, for a given s_l and L, the probability that a good in group l does comply is given by $p_l(s_l) \equiv F_l(c^{-1}(s_l L))$. Given that F_l is a cdf and $c(.)$ is an increasing function,[18] we have $p_l'(s_l) > 0$. In addition, we assume that $p_l''(s_l) < 0$.

The inspecting agency faces uncertainty (ambiguity) with respect to the compliance of shipments in each group. Under standard subjective expected utility theory (with subjective

[17] This setup can also be used to model a customs agency's problem of minimizing the expected number of firms that misreport customs declarations. To see this, consider the following. There are traded goods that arrive to the country's border and there are tariffs imposed on these goods. Depending on its type, y, the good can be a low tariff item or a high tariff item. Each firm declares its type and its tariff is determined accordingly. Assume that $c(y)$ represents the benefit the firm receives from understating its type. To prevent misreporting, the customs agency searches the content of imported goods to see whether their actual type matches with their declared type. After a search, if a firm is found to be misreporting, it incurs a loss of \$$L$. There is a resource constraint on the maximum number of searches that can be performed, which is given by $\overline{S}$.

[18] Since $c' > 0$, we have $c^{-1\prime} > 0$.

probabilities as in Savage, 1954), the agency assigns a probability distribution over the set of possible events and chooses an action from the available set to maximize its expected utility. However, this approach was challenged by the Ellsberg paradox (Ellsberg, 1961) in which people's choices violate a postulate of subjective expected utility, the Sure-Thing-Principle.[19] In contrast, here we assume that the inspecting agency has some belief about the compliance of goods in each group, but lacks confidence in its belief. As a result, the agency may react to ambiguity by developing optimistic and pessimistic attitudes towards the compliance of goods. While optimistic beliefs cause the overweighting of positive outcomes, i.e., compliance, pessimistic beliefs result in the overweighting of negative outcomes, i.e., no compliance.

In order to model this ambiguity, we consider a specific type of capacity for the agency's beliefs about compliance, a neo-additive (non-extremal-outcome-additive) capacity. A capacity is a normalized monotone set function that maps events to real numbers. A neo-additive capacity is a non-additive capacity that consists of a convex combination of an additive capacity,[20] and a special type of non-additive capacity that only distinguishes between whether an event is impossible, possible or certain, which is called Hurwicz capacity by Chateauneuf, Eichberger and Grant (2007).[21] Non-additivity permits us to analyze different attitudes toward ambiguity. Specifically, a convex capacity corresponds to pessimism whereas a concave

[19] According to the Sure-Thing-principle, if an individual takes a certain action when an event occurs as well as when it does not occur, then he/she should take the same action even if he/she does know nothing about that event's occurrence. We can use an example of Ellsberg Paradox to show how this principle is violated. Consider two urns. In Urn 1, there are 5 red and 5 blue marbles. Urn 2 has 10 marbles with red and blue colors in unknown proportions. People engage in 2 gambles. In Gamble 1, they receive \$20 if they draw a blue marble and nothing if they draw a red marble, whereas in Gamble 2, they receive \$20 if they draw a red marble and nothing if they draw a blue marble. Each person can choose which urn to draw from. It turns out that most people choose to draw from Urn 1 in both gambles, which is inconsistent with the Sure-Thing-Principle. This is so since according to this principle, if one chooses Urn 1 for Gamble 1, then the same person must choose Urn 2 for Gamble 2 or *vice versa*. For more on Ellsberg paradox and experimental evidence, see Camerer (1995).

[20] A capacity is additive when it is both concave and convex. Consider a capacity v and 2 events A and B. Additivity implies

$$v(A \cup B) = v(A) + v(B) - v(A \cap B).$$

For example, probability distributions are additive.

[21] We consider only the empty set as impossible or null and only the whole state space as certain.

capacity corresponds to optimism.[22]

Formally, we represent the inspecting agency's belief about the likelihood of a good's compliance in group l with a neo-additive capacity v based on $\{p_l, 1-p_l\}$ as[23]

$$v_l(p_l(s_l)) = \delta_l\alpha_l + (1-\delta_l)p_l(s_l), \tag{1}$$

where δ_l, $\alpha_l \in [0, 1]$ represent the agency's ambiguity and the degree of optimism with regards to group l, respectively. In plain words, ambiguity measures uncertainty about the underlying probability that a shipment of a good in group l is compliant with regulations. When facing ambiguity, the agency might have a positive (optimistic) or negative (pessimistic) attitude towards the compliance of goods. Higher δ_l's mean more ambiguity, higher α_l's mean that the agency is more optimistic. We normalize $v_l(0) = 0$ and $v_l(1) = 1$. Similarly, the inspecting agency's belief about the likelihood of no compliance of any good in group l is given by

$$v_l(1-p_l(s_l)) = \delta_l\alpha_l + (1-\delta_l)\left[1-p_l(s_l)\right]. \tag{2}$$

Note that in general $v_l(p_l(s_l)) + v_l(1-p_l(s_l)) \neq 1$, unless $\delta_l = 0$ or $\alpha_l = \frac{1}{2}$.

4 Equilibrium

We will use an asterisk (*) to denote equilibrium values. The inspecting agency is assumed to have Choquet Expected Utility preferences. The objective of the inspecting agency is to minimize the expected number of *undetected* non-compliant shipments subject to its resource constraint. This in turn minimizes the HSE risk the importing country faces. Throughout the analysis, we will assume the existence of an interior solution.

Before starting our analysis, it is helpful to describe the main framework for Choquet Expected Utility theory. By using this particular framework, we can incorporate the inspecting agency's optimistic and pessimistic attitudes towards uncertainty. The decision weights

[22] In general, neo-additive capacities are neither convex nor concave. However, as shown by Chateauneuf, Eichberger and Grant (2007), the 'multiple-prior' representation of neo-additive capacities allows a separation between ambiguity and attitudes towards ambiguity, i.e., pessimism and optimism.

[23] Further details of neo-additive capacity and the Choquet integral is provided in the appendix.

used in the computation of the Choquet integral will overweight better (worse) outcomes if the capacity is concave (convex). It is therefore well-suited to model such responses to ambiguity as optimism and pessimism.

Given the inspecting agency's beliefs in (1) and (2), its Choquet Expected Utility (for a specific utility function based on the inspecting agency's objective) of searching group l with intensity s_l is

$$V_{p_l}(s_l) = \delta_l \alpha_l M(s_l) + \delta_l(1-\alpha_l)m(s_l) + (1-\delta_l)E_{p_l}(s_l), \tag{3}$$

where $M(s_l)$, $m(s_l)$, and $E_{p_l}(s_l)$ denote the maximum utility, the minimum utility and the expected utility with respect to p_l, respectively, of searching group l with intensity s_l. Next, we turn to the inspecting agency's problem.

4.1 Minimizing the expected number of *undetected* non-compliant shipments

We assume that the inspecting agency wants to minimize the expected number of *undetected* non-compliant shipments. Since, with search, the non-compliant good is identified with probability one, goods that go through search cannot cause any harm to the economy (because the inspection resolves the HSE risk). As a result, focusing search efforts to minimize the expected number of undetected non-compliant shipments also minimizes the HSE risk.

Based on equation (3), the first task is to determine the maximum utility, minimum utility and the expected utility in accordance with this objective function. The maximum utility is obtained in the best case outcome in which if S_l number of searches are performed in group l, all of the remaining shipments which are not searched in group l comply:

$$M(s_l) = 0, \tag{4}$$

On the other hand, the minimum utility is obtained in the worst case outcome where if S_l number of searches are done in group l, none of the remaining shipments which are not searched comply:

$$
\begin{aligned}
m(s_l) &= N_l - S_l, \text{ or} \\
m(s_l) &= N_l(1 - s_l). \qquad (5)
\end{aligned}
$$

Finally the standard expected utility with respect to p_l can be found as

$$
\begin{aligned}
E_{p_l}(s_l) &= (1 - p_l(s_l))(N_l - S_l), \text{ or} \\
E_{p_l}(s_l) &= N_l[(1 - s_l)(1 - p_l(s_l))]. \qquad (6)
\end{aligned}
$$

Substituting (4), (5) and (6) into (3) allows the objective function to be rewritten as

$$
\begin{aligned}
V_{p_l}(s_l) &= \delta_l(1 - \alpha_l)N_l(1 - s_l) + (1 - \delta_l)(1 - p_l(s_l))N_l(1 - s_l), \text{ or} \\
&= N_l(1 - s_l)\left[\delta_l(1 - \alpha_l) + (1 - \delta_l)(1 - p_l(s_l))\right].
\end{aligned}
$$

Notice that the term in the square brackets shows the overall belief about non-compliance. It consists of the weighted average of pessimism in the belief that no one complies and the expected probability of compliance, where the weights are based on the ambiguity parameter. The minimization problem can be written as

$$
\min_{s_1, s_2 \in [0,1]} \sum_{l=1}^{2} V_{p_l}(s_l) + \lambda\left(\overline{S} - N_1 s_1 - N_2 s_2\right).
$$

Taking first order condition with respect to s_l, we obtain[24]

$$
-\left[\delta_l(1 - \alpha_l) + (1 - \delta_l)(1 - p_l(s_l^*))\right] - (1 - \delta_l)(1 - s_l^*)p_l^{'}(s_l^*) = \lambda,
$$

where on the left-hand side, the first term represents the change in the proportion of unsearched shipments while keeping the overall belief on their non-compliance constant, and the second term is the change in the overall belief about the non-compliance of unsearched shipments while keeping their proportion constant. In other words, following a marginal increase in search intensity, the first term represents the direct effect of search in reducing undetected non-compliant shipments, whereas the second term shows the indirect effect of a

[24]Note that since $p_l^{'}(s_l) > 0$ and $p_l^{''}(s_l) < 0$, the second order condition is satisfied.

change in the overall belief of non-compliance through the change in unsearched importers' response to search.[25] The magnitude of this indirect effect critically depends on the agency's uncertainty about the underlying probability distribution such that the more uncertainty there is (higher δ_l), the less will be the change through this indirect effect.

After some manipulation, the first order conditions with respect to s_1 and s_2 imply

$$\begin{aligned} &\delta_1 (1-\alpha_1) + (1-\delta_1)\left[1 - p_1(s_1^*) + (1-s_1^*)p_1'(s_1^*)\right] \\ &= \delta_2 (1-\alpha_2) + (1-\delta_2)\left[1 - p_2(s_2^*) + (1-s_2^*)p_2'(s_2^*)\right]. \end{aligned} \tag{7}$$

The equilibrium is determined according to (7) together with $N_1 s_1^* + N_2 s_2^* = \overline{S}$.

Some observations are in order. First, when $\delta_1 = \delta_2 = 0$ (no ambiguity), then we have standard expected utility maximization with full confidence. The equilibrium is determined according to

$$1 - p_1(s_1^*) + (1-s_1^*)p_1' = 1 - p_2(s_2^*) + (1-s_2^*)p_2', \tag{8}$$

together with $N_1 s_1^* + N_2 s_1^* = \overline{S}$.

Second, when $\delta_1 = \delta_2 = 1$ (full ambiguity), if $\alpha_i < \alpha_j$ then we have $s_i^* = \frac{\overline{S}}{N_i}$ and $s_j^* = 0$. In case α's are identical, we have infinitely many equilibria such that any $s_l^* \in [0, \frac{\overline{S}}{N_l}]$ can be equilibrium as long as $\sum_{l=1}^{2} N_l s_l = \overline{S}$. In other words, all search effort is directed towards the group in which the agency is relatively more pessimistic.

Third, if we assume $F_1 = F_2$, $\alpha_1 = \alpha_2$ and $\delta_1 = \delta_2 < 1$, then we obtain $s_1^* = s_2^*$.

4.2 Comparative Statics

Consider the condition given in (7), where $s_2 = \frac{\overline{S} - N_1 s_1}{N_2}$. A closer look at this expression shows us that $\frac{\partial s_i^*}{\partial \alpha_i} < 0$ and $\frac{\partial s_j^*}{\partial \alpha_i} > 0$. This means the search intensity of group i increases (while that of group j decreases) whenever the inspecting agency becomes less optimistic

[25] To draw a contrast between our paper and those of Knowles *et al.* (2001) and Persico (2002), if we were to analyze a single inspecting officer's problem this indirect effect would be absent since the single officer would not take into account the effect of his search effort on the change in the overall belief about the non-compliance of undetected shipments.

towards group i. In addition, at $s_l = s_l^*$ we have

$$N_i \frac{\partial s_i^*}{\partial \delta_i} = -N_j \frac{\partial s_j^*}{\partial \delta_i} = \left\{ \begin{array}{l} > 0, \text{ if } 1 - \alpha_i > 1 - p_i(s_i^*) + (1 - s_i^*)p_i^{'} \\ < 0, \text{ if } 1 - \alpha_i < 1 - p_i(s_i^*) + (1 - s_i^*)p_i^{'} \\ = 0, \text{ if } 1 - \alpha_i = 1 - p_i(s_i^*) + (1 - s_i^*)p_i^{'} \end{array} \right\} \tag{9}$$

This condition implies that an increase in ambiguity of group i increases (decreases) the search intensity of group i, whenever the magnitude of the pessimism in the belief is larger (smaller) than the effect of a marginal increase in search intensity on the compliance of the proportion of unsearched importers. Intuitively, there are two opposing forces. On the one hand, for a given pessimistic belief about compliance of a group, an increase in ambiguity of that group calls for an increase in search intensity. On the other hand, search serves to discourage non-compliant behavior and as ambiguity increases for a particular group, this deterrent effect of searching shipments in that group becomes less relevant.[26] The result depends on which force dominates. Further, due to the binding resource constraint, as one group's search intensity increases (decreases), the other group's search intensity decreases (increases).

We can also look at what happens to the expected compliance of *unsearched* shipments when ambiguity decreases proportionally across groups. Assume that F_1 and F_2 are indeed the true distributions of groups 1 and 2, respectively. In that case, the optimal allocation of search intensity that minimizes the expected number of non-compliant *undetected* shipments is given by condition (8). If this condition is satisfied even in the presence of ambiguity, then it is not possible to improve the compliance further and reduction in ambiguity has no effect. Therefore, consider the scenario in which due to ambiguity, condition (8) does not hold. We can state the following proposition.

Proposition *Assume F_1 and F_2 are true distributions of groups* 1 *and* 2*, respectively. A proportional decrease in ambiguity that leaves $\frac{\delta_1}{\delta_2}$ constant improves the expected compliance of unsearched shipments.*

[26] Search affects the probability of compliance, but more ambiguity means less confidence about the underlying probability distribution.

Proof. Dividing both sides of equation (7) by δ_2, we have

$$\begin{aligned}&\tfrac{\delta_1}{\delta_2}(1-\alpha_1)+\left(\tfrac{1-\delta_1}{\delta_2}\right)\left[\underbrace{1-p_1(s_1^*)+(1-s_1^*)p_1^{'}(s_1^*)}_{\text{Denote by } I}\right]\\ &=(1-\alpha_2)+\left[\tfrac{1-\delta_2}{\delta_2}\right]\left[\underbrace{1-p_2(s_2^*)+(1-s_2^*)p_2^{'}(s_2^*)}_{\text{Denote by } J}\right].\end{aligned} \tag{10}$$

As a result of an equal percentage decrease in δ_1 and δ_2, the first term on both sides of the equation does not change. The change can come from the difference in the relative magnitude of I and J terms, where I and J are defined in the above equation. We also know from condition (8) that the expected number of non-compliant undetected shipments are minimized when $I = J$. Therefore, if $I = J$ holds even in the presence of ambiguity, then it is not possible to improve the compliance further and reduction in ambiguity has no effect. To see the effect of a proportional reduction in ambiguity, our focus is on cases in which $I \neq J$.

We need to show that a proportional decrease in ambiguity for both groups that leaves $\frac{\delta_1}{\delta_2}$ constant brings I and J terms closer. To that purpose, assume that $I > J$. In this case, following an equal percentage decrease in δ_1 and δ_2, holding I and J constant, the left-hand side of the equation (10) goes down more than the right-hand side of the same equation. To establish equality again, $I - J$ must go down. Notice that in the limit when ambiguity is completely eliminated, we have $I - J \rightarrow 0$. The analysis of $I < J$ follows similar steps. ■

5 Empirical evidence

In this section we offer empirical evidence on inspection rates to support our argument that ambiguity plays a role in border management agencies' decision to inspect a shipment. Ambiguity is not an observable variable, of course, and so we can only offer indirect evidence. We argue that a key source of ambiguity for inspections of imported goods is that many combinations of import shipment characteristics are observed very infrequently by the inspecting agency. Infrequency limits the ability of the agency to have fully informed *ex ante* beliefs about the probability that a shipment arriving at the border with those characteristics violates some regulation for imported goods. Lagged shipment frequency is therefore a good (inverse) proxy for ambiguity.

In our exercise we attempt to control for inspecting activity that would have occurred if the agency's inspection decision were based solely on expected utility theory, and then show an additional effect of ambiguity on inspection activity. Under expected utility theory, the inspecting agency would be assumed to be fully informed about the probability distribution underlying the conditional likelihood that a shipment is not compliant with import regulations. If the fixed effects we include in our specification control for variation across shipments in expected probabilities of non-compliance and for variation in expected harm, there should be no role for lagged shipment frequency in our regressions. If, however, ambiguity affects the inspection decision – and if the agency has more ambiguity about shipments that have been observed less frequently in past years – then the number of lagged shipments would enter the agency's inspection model, and be revealed in regressions linking observed inspection rates with lagged shipment frequency. Using data from the Serbian Customs Administration, we show that inspection rates in a given year – for shipments from a given combination of HS-6 product, origin country, and importing firm triplet – are negatively correlated with the frequency that shipments with the same characteristics were observed in the previous year. In a robustness exercise, we show that these effects persist if lagged shipment frequencies are defined over three year periods, rather than one.

5.1 Data and Empirical Specification

We use Serbian import data from 2006-16, which were provided by the Serbian Customs Administration. The data are defined at the level of an import declaration (hereafter, a shipment). Each shipment record contains information about the shipment's value, weight, origin country, associated duties and taxes paid, as well the importing firm's identity, a 10 digit Harmonized System product code and the type of inspection that was conducted, if any. Firms are identified by their unique tax identification number, and we consider a product to be defined by its HS6 code.[27] We further restrict the data to imports of products that will be consumed in Serbia and exclude imports that are temporary, for inward processing or for re-export.

A key outcome for each shipment is whether or not it is inspected. In Serbia, each shipment is subject to a possibility of six classes of documentary and/or physical inspections: (1) Inspection not obligatory, (2) Documentary, (3) Partial physical, (4) Complete physical, (5) Partial physical and documentary, and (6) Complete physical and documentary. We construct two definitions of inspections: the narrow definition includes any type of physical inspections (types 3-6), and the broad definition includes both documentary and physical inspections (types 2-6). Inspection type 2, Documentary inspections, represents a small share of all inspection activity, so our results are similar across the broad and narrow treatments. We report results for the broad definition of inspections, which includes documentary inspections in the calculation of inspection rates.[28]

The key variables are constructed by aggregating over individual shipments to produce annual numbers of shipments and inspected shipments for each triplet of origin-country (o), importing firm (f), and product (k). Because our purpose is to control, as best we can, for parameters that would explain variation in inspection rates in an expected utility setting, we include fixed effects in our specification. Our primary interest is in the relationship between current-year inspection rates in a product-origin country-firm triplet and lagged numbers of shipments in that triplet. In order to do so flexibly, we create bins of different shipment frequencies and estimate the effects of dummy variables attached to each frequency bin. Our frequency bins, have, respectively, 0, 1, 2, 3-5, 6-10, 11-100, and 100+ lagged shipments. Our outcome variable is the inspection rate, which is calculated as the ratio of inspected shipments to shipments in year t, for an ofk triplet, multiplied by 100.

[27] We would prefer to use HS10 codes, but the data use three revisions of the HS classifications (HS2002 for the data in 2006, HS2007 for 2007-11 and HS2012 for data in 2012-16). We concord the data at the HS6 level using the concordance table provided by the World Integrated Trade Solution (WITS).

[28] We exclude from the data shipments that are never inspected due to their product characteristics: trade in natural gas or electricity transported through pipelines and electrical power lines. These shipments are distinct from shipments that are not subjected to physical inspections through a determination of the customs agency (type 1).

Our regression is as follows:

$$IR_t^{ofk} = \mathbf{\Theta}\ \mathbf{Bin^{ofk}_{(t-1)}} + \gamma_t^{ok} + \delta_t^f + \varepsilon_t^{ofk},$$

where IR_t^{ofk} is the inspection rate for a given *ofk* triplet in year t, $\mathbf{\Theta}$ a vector of regression coefficients, each associated with one of the dummy variables in $\mathbf{Bin^{ofk}_{(t-1)}}$, a vector of lagged shipment frequency dummies, γ_t^{ok} is a product-country fixed effect, δ_t^f a firm fixed effect, and ε_t^{ofk} a normally distributed error term. We estimate our regressions with and without firm fixed effects, for the years 2007 and 2016, and for the entire sample.

5.2 Identification Strategy and Limitations

The evidence that we present is meant to be indicative of the role for ambiguity in the customs environment, but we cannot be conclusive on this point. Our identification strategy has two main difficulties. First, ambiguity is not an observable variable. Second, we lack evidence in these data on past compliance rates, which is information that a customs agency would have and would incorporate in its inspection model. We believe that lagged shipments are a useful proxy for ambiguity because the inspecting agency has less information about shipment types with which they have less experience; but it may also be that less frequent shippers are less often compliant. Our evidence would be more compelling if we could include past compliance rates as a control variable, and still find an effect of lagged shipment frequency on inspection rates.[29] That said, our use of lagged shipment variables as an ambiguity proxy likely understates the role of ambiguity because we ignore sources of ambiguity that are not tied to lagged shipment frequency, especially those that are swept out by product-country fixed effects.

Our identification strategy is to use fixed effects to remove obvious sources of variation that would drive the inspection decision in an expected utility framework, while retaining some variation in the data that allows us to observe the effects of lagged shipment frequency on the current inspection rate. If the agency's risk model were constructed under an expected

[29] Inspection outcomes are sensitive information and we do not have them in the data provided by the Serbian Customs Administration.

utility framework, that model would reflect both expected harms from non-compliance and conditional expectations of the likelihood of non-compliance for each combination of shipment characteristics. It seems likely that most of the variation in these two parameters would arise at either the product and/or origin-country level, and we include product-country fixed effects to control for variation of this sort.

In the specifications without firm dummies our identification comes from variation that is both across importing firms and within firms that import in more than one product-country pair. In these specifications we assume that variation across firms in inspection frequency occurs not because less frequent importers have higher likelihoods of non-compliance, but rather because the customs agency has observed shipments imported by these firms less often, and wishes to inspect their shipments more frequently in order to inform its own expectation about their compliance rates.

In order to take into account the possibility that firms that import more frequently are more compliant, on average, we also estimate specifications that include firm fixed effects. In these specifications most of the variation in the data is absorbed by the fixed effects. The variation that remains to be exploited is within-firm and across combinations of products and countries. In these specifications, the fixed effects control for variation across firms in the inspection rate, but an effect of lagged shipment frequency can still be revealed if origin country-product combinations in which the firm ships less frequently are more commonly inspected, relative to average inspection rates in those product-country pairs.

We also estimate regressions that pool across years, and in these regressions we use both product-country-year and firm-year fixed effects. Product-country-year dummies control for year-to-year changes in the assessment of risks posed at the level of this triplet. Firm-year fixed effects control for updating over time of the parameters in the risk model associated with the importing firm. Residual variation within firms, but across product-country-year triplets, are central to identifying an effect of lagged shipment frequency on inspections.

5.2.1 Results

Summary statistics for the 2007-16 data are presented in Table 1. The mean annual number of import shipments per combination of importing firm, origin country, and product is 5.5, and the mean number of inspections per triplet is 0.44. The mean inspection rate is 9.1 percent. 55 percent of *ofk* triplets had not been observed in the previous year. 92 percent of observations had 10 or fewer shipments observed in the prior year. Without IT, it would be difficult for the Serbian customs agency to develop good conditional forecasts of expected compliance in this setting.

Table 1: Summary Statistics for 2007-16

	N	Mean	SD	Min	Max
Shipments	5198939	5.50	22.41	1.00	14301.00
Inspections	5198939	0.44	5.06	0.00	2453.00
Inspection rate	5198939	9.09	26.54	0.00	100.00
$Bin_{n=0}$	5198939	0.55	0.50	0.00	1.00
$Bin_{n=1}$	5198939	0.13	0.33	0.00	1.00
$Bin_{n=2}$	5198939	0.07	0.26	0.00	1.00
$Bin_{n\in[3-5]}$	5198939	0.11	0.31	0.00	1.00
$Bin_{n\in[6,10]}$	5198939	0.06	0.24	0.00	1.00
$Bin_{n\in[11,100]}$	5198939	0.08	0.26	0.00	1.00
$Bin_{n>100}$	5198939	0.00	0.07	0.00	1.00

Summary statistics for Serbian Customs data from 2007-2016. Annual data organized at the level of HS-6 product, origin country and importing firm. *Bin* variables are dummy variables indicating the frequency of shipments in the product-country-firm triplet in the previous year. Subscripts on the bin dummies indicate ranges of the number of lagged shipments associated with the dummy variable for that bin.

The dependent variable in our regressions is the inspection rate, where inspections are defined to include documentary inspections. The independent variables are dummy variables indicating shipment frequency. The dummy variable associated with 0 lagged shipments in the previous year is omitted from the regression.

Table 2 reports results for the broad definition of the inspection rate variable. Inspection rates fall as the lagged number of shipments rises. When we exclude firm fixed effects, we find that observations in which shipments were observed in the prior year generate between

Table 2: Inspection rates and lagged shipment frequency

	2007	2007	2016	2016	2007-16	2007-16
$Bin_{n=1}$	-2.299***	-0.017	-2.286***	-0.012	-2.461***	-0.029
	(0.125)	(0.108)	(0.095)	(0.070)	(0.048)	(0.028)
$Bin_{n=2}$	-2.607***	-0.037	-2.597***	-0.093	-2.812***	-0.105***
	(0.153)	(0.136)	(0.110)	(0.080)	(0.060)	(0.034)
$Bin_{n\in[3-5]}$	-2.699***	-0.037	-3.197***	-0.078	-3.215***	-0.136***
	(0.135)	(0.114)	(0.115)	(0.068)	(0.071)	(0.032)
$Bin_{n\in[6-10]}$	-2.897***	-0.011	-3.456***	-0.118*	-3.590***	-0.176***
	(0.167)	(0.135)	(0.133)	(0.072)	(0.092)	(0.040)
$Bin_{n\in[11-100]}$	-2.971***	-0.235	-3.878***	-0.212***	-4.173***	-0.397***
	(0.202)	(0.157)	(0.144)	(0.078)	(0.122)	(0.069)
$Bin_{n>100}$	-7.325***	-2.179***	-5.803***	-0.970***	-6.432***	-1.495***
	(0.892)	(0.658)	(0.321)	(0.242)	(0.355)	(0.292)
Product x Origin	Yes	Yes	Yes	Yes	No	No
Product x Origin x Year	No	No	No	No	Yes	Yes
Firm	No	Yes	No	Yes	No	No
Firm x Year	No	No	No	No	No	Yes
R^2	0.336	0.588	0.409	0.656	0.398	0.656
Adjusted-within-R^2	0.002	0.000	0.006	0.000	0.005	0.000
N	481271	474641	584179	578042	4929671	4867437

Table notes: Regressions for individual years 2007 and 2016, and pooled regressions over the entire 2007-2016 period. Data are annual totals or rates calculated for triplets defined by shipments associated with a given combination of HS6 product, origin country and importing firm. The dependent variable is the inspection rate. The independent variables are dummy variables indicating lagged shipment frequency bins. Bins are defined for $n = 0$, 1, 2, 3-5, 6-10, 11-100 and >100 shipments in the year prior to the inspection decision. The dummy variable indicating observations with 0 lagged shipments is omitted from the regression. Standard errors are clustered by Product × Origin Country and reported in brackets. The symbols ***,**,* represent significance at the 1%, 5%, and 10% level.

2 and 7 fewer inspections per hundred shipments than among observations with 0 lagged shipments in the prior year. Relative to an average inspection rate of 9.09, the estimated differences in inspection rates across bins are quantitatively large. All six bins that saw shipments in the prior year have inspection rates that are statistically different than the inspection rate in the bin with no lagged shipments.

When we include the importing firm fixed effect, the effects of lagged shipment frequency are weaker and less significant, though observations with more than 100 lagged shipments in the previous year are still less likely to be inspected than those with zero lagged shipments.

When we pool over multiple years we find slightly stronger effects of lagged shipment frequency, and these effects are almost always highly statistically significant, whether or not we include firm-year fixed effects.

The results in Table 2 use one year's worth of lagged shipments as the (inverse) proxy for ambiguity. Serbian Customs has modern IT systems that are able to store information indefinitely and recall it quickly. It might be better therefore to define the ambiguity proxy as the agency's recorded history of shipments in a given product-country-firm combination. The information we have is not exhaustive in that regard, but we do have data that allow us to use longer lag-periods for defining the ambiguity proxies. In a robustness exercise, we define the lag period in terms of three-year spans rather than one, and estimate the relationship between inspection rates and the frequency bins defined by the longer lag periods.

The results appear in Table 3.[30] The coefficient estimates are broadly similar to those from regressions using single year lag-periods. We conclude that lagged shipment frequency defined over a single year is a suitable proxy for shipment histories with longer lags.

6 Calibration/Numerical simulation

In order to illustrate the operation of the model in the portion of the parameter space that is most relevant for operational risk management reforms, we calibrate the model to Serbian data for 2016 and conduct counterfactual analysis. We believe our model is most useful in a pre-reform setting, where an *ex ante* analysis may help policymakers understand the potential benefits of IT-led risk management reforms. But the data we have available are from Serbian customs, which already engages in sophisticated risk management. We are therefore calibrating to a post-reform setting.

To provide a quantitative guide to the implications of risk management reform, we consider a reverse reform, and do so in two segments. First, we simulate the removal of advanced IT systems by substantially increasing ambiguity, while holding fixed the aggregate number

[30] We estimate for 2009, rather than 2007, since it is the earliest date possible to use a three-year lag-period in the sample.

Table 3: Inspection rates and lagged shipment frequency (3-year lag intervals)

	2009	2009	2016	2016	2009-16	2009-16
$Bin_{t\to 3,n=1}$	-2.143***	0.182*	-2.135***	0.071	-2.328***	0.022
	(0.127)	(0.110)	(0.111)	(0.087)	(0.054)	(0.036)
$Bin_{t\to 3,n=2}$	-2.559***	0.036	-2.420***	-0.110	-2.632***	-0.060
	(0.155)	(0.128)	(0.128)	(0.102)	(0.065)	(0.042)
$Bin_{t\to 3,n\in[3-5]}$	-2.880***	-0.174*	-2.788***	-0.131*	-2.973***	-0.112***
	(0.122)	(0.100)	(0.110)	(0.076)	(0.066)	(0.033)
$Bin_{t\to 3,n\in[6-10]}$	-3.349***	-0.170	-3.003***	-0.083	-3.317***	-0.116***
	(0.129)	(0.104)	(0.117)	(0.075)	(0.080)	(0.034)
$Bin_{t\to 3,n\in[11-100]}$	-4.253***	-0.383***	-3.586***	-0.130**	-3.980***	-0.248***
	(0.126)	(0.097)	(0.124)	(0.062)	(0.106)	(0.043)
$Bin_{t\to 3,>100}$	-6.546***	-1.888***	-4.726***	-0.425***	-5.535***	-0.904***
	(0.433)	(0.345)	(0.220)	(0.134)	(0.226)	(0.153)
Product x Origin	Yes	Yes	Yes	Yes	No	No
Product x Origin x Year	No	No	No	No	Yes	Yes
Firm	No	Yes	No	Yes	No	No
Firm x Year	No	No	No	No	No	Yes
R^2	0.362	0.641	0.409	0.656	0.412	0.673
Adjusted-within-R^2	0.006	0.000	0.006	0.000	0.006	0.000
N	446809	440314	584179	578042	3950653	3902077

Table notes: Regressions for individual years 2009 and 2016, and pooled regressions over the entire 2009-2016 period. Data are annual totals or rates calculated for triplets defined by shipments associated with a given combination of HS6 product, origin country and importing firm. The dependent variable is the inspection rate in the relevant year. The independent variables are dummy variables indicating shipment frequency bins defined over a three year period prior to the year in which inspection rates are defined. Bins are defined for $n = 0$, 1, 2, 3-5, 6-10, 11-100 and >100 shipments. The dummy variable indicating observations with 0 lagged shipments is omitted from the regression. Standard errors are clustered by Product × Origin Country and reported in brackets. The symbols ***,**,* represent significance at the 1%, 5%, and 10% level.

of searches. Increasing ambiguity magnifies the misallocation of search activity, and reduces aggregate compliance. In the second stage we raise the level of total search activity until the level of aggregate compliance is restored. Our purpose is to develop a quantitative understanding of the relationship between changes in ambiguity and compensating changes in search intensity.

Although we calibrate to actual data on inspection activity, our calibration remains a stylized example. In an actual risk management reform, especially one occurring in a customs agency, there would be enormous heterogeneity – across countries, products and firms – in certain model parameters, and in observed outcomes.[31] In this calibration we shut down much of this variation, focusing solely on the channels that we have heretofore isolated, the link between infrequent shipments and ambiguity, and ambiguity's contribution to the misallocation of search activity.

6.1 Computational model

In section 5 we observed an inverse relationship between inspection rates and lagged shipment frequency. Under our working hypothesis that lagged shipment frequency is an inverse proxy for ambiguity, our objective function can produce this negative relationship under certain conditions. Consistent with this objective, in our numerical simulation the agency's goal is to minimize the HSE risk (and, equivalently, minimize expected non-compliance among *unsearched* shipments). We offer a brief restatement of the model using this framework.

The Lagrangian associated with the optimization of the objective function is

$$\min_{s_l \in [0,1]} \mathcal{L} = \sum_l N_l(1 - s_l)\left[\delta_l(1 - \alpha_l) + (1 - \delta_l)(1 - p_l(s_l))\right] + \lambda(\overline{S} - \sum_l N_l s_l). \tag{11}$$

A key variable in this expression is the probability of compliance $p_l(s_l) \equiv F_l\left(c^{-1}(s_l L)\right)$. Numerical solution of the equilibrium requires assumptions about the underlying distribution of the attribute of shipments in each bin, F_l, as well as the attribute-dependent costs of compliance, $c(y)$. We begin by assuming a functional form for compliance costs: $c(y) = y$, where attribute y is a realization of a random variable Y_l with the cdf of F_l and the pdf of f_l. This functional form implies $c^{-1}(y) = y$ and hence $p(s_l) \equiv F_l\left(s_l L\right)$. In our numerical exercise, we assume that the attribute of shipments follows an identical distribution across bins. In particular, we simulate our model using the Pareto distribution with a scale parameter of b

[31]The non-customs agencies – that is, the 'technical agencies' such as those responsible for sanitary and phytosanitary standards – oversee a smaller range of products and, in some cases, one might expect less variation in the their implied model parameters. Implementation of risk management in technical agencies represents the next wave of reform in border management, and a simplified model may be more representative of the issues in future risk management reforms. See Fernandes *et al.* (2017) for a discussion of risk management reform in technical agencies.

and shape parameter of 1. The equations for $p_l(s_l)$ and $p_l'(s_l)$ thus take the form:

$$p_l(s_l) = p(s_l) = \begin{cases} 1 - \frac{b}{s_l L}, \text{ for } s_l \geqslant \frac{b}{L} \\ 0, \text{ for } s_l < \frac{b}{L}, \text{ and} \end{cases} \tag{12}$$

$$p_l'(s_l) = p'(s_l) = \begin{cases} \frac{b}{s_l^2 L}, \text{ for } s_l \geqslant \frac{b}{L} \\ 0, \text{ for } s_l < \frac{b}{L}. \end{cases} \tag{13}$$

For purposes of accounting we add another equation to the model that keeps track of compliance across the entire system:

$$p_{tot} = \frac{\sum_l N_l p\left(s_l\right)}{\sum_l N_l}. \tag{14}$$

The numerator of this expression is the sum over the number of compliant shipments in each bin, and the denominator is the sum over the number of shipments in each bin.

Equilibrium values of s_l are continuous rates, and are not required to be chosen to imply a discrete number of inspections in each bin. We do not interpret N as the literal number of shipments, but rather a representation of relative sizes of the number of shipments within each bin.[32] The values of s_l and p_l should therefore be interpreted as continuous rates.

Equations (11), (12), (13), and (14) define the computational model used in our exercises.[33]

6.2 Data summary

We report the data that we seek to replicate in Table 4. Using the lagged shipment frequency bins we defined in section 5, we calculate key summary statistics from the 2016 data, statistics that we seek to match in our numerical model. The summary statistics we calculate are: 1) the total share of 2016 shipments in each bin, 2) the average number of lagged shipments (across product-country-firm combinations) in each bin, 3) the number of

[32] We normalize the total number of shipments N to 100, and allocate shipments across bins according to their proportions in the data.

[33] Formally, we use a mixed complementarity program to solve a system of first-order Kuhn-Tucker conditions linked to the constrained optimization problem. Our program is solved in the GAMS software.

Table 4: Data to be calibrated

Frequency of lagged shipments in bin	0	1	2	3-5	6-10	11-100	100+
Share of total 2016 shipments	0.170	0.047	0.036	0.079	0.086	0.374	0.208
Inspections per 100 shipments	14.6	6.7	6.7	6.2	5.9	5.8	5.6
Mean no. of lagged shipments	0	1	2	3.8	7.6	27.3	212.9
Total inspections per 100 shipments				7.3			

Author calculations using Serbian Customs data from 2016.

inspections conducted per 100 shipments in each bin, and 4) the number of inspections per 100 shipments in aggregate.[34]

In aggregate, the inspection rate in 2016 was 7.3 inspections per 100 shipments.[35] The key lesson from Table 4 is that the inspection rate is much higher for shipments that were not observed in the previous year (14.6 percent of shipments) than for shipments in the other five bins. Moreover, the bin-level inspection rate is weakly monotonic and decreasing across the lagged shipment frequency bins. Bins with shipment types that were seen more often in 2015 have lower average inspection rates in 2016.

Also important for calibration are the bins' shares of overall shipment activity. Table 4 shows that most of the shipment activity occurs at either end of the lagged shipment frequency distribution. At the upper end, shipments that were observed between 11-100 times in 2015 made up 37.4 percent of all shipments in 2016, and shipments that had been observed more than 100 times accounted for an additional 20.8 percent of all shipments. At the lower end of the distribution, shipments that were not observed at all in the previous year made up 17 percent of all shipments.[36]

We also calculate the mean number of lagged shipments per bin, a numerical value we use in calibrating ambiguity. The first three lagged shipment bins are made up entirely of observations with exactly zero, one, or two lagged shipments, respectively. In the last four bins, we average over *ofk* triplets that have varying levels of lagged shipment frequencies.

[34] As in the econometric estimates we report, inspections are defined broadly, notably including documentary inspections.

[35] Table 1 reports an average inspection rate of 9.1 across the years 2007-2016. 7.3 inspections per 100 shipments is the 2016 rate.

[36] Trade flows are exogenous in our model, and we match all of the shipment bin weights exactly in our model calibration.

The mean for each bin is reported in row 3 of Table 4.

6.3 Parameterization

The central claim of this paper is that ambiguity plays a critical role in the allocation of search activity in the international trade setting. Border agencies deal with imports from an extremely large number of combinations of countries, products, and firms. The sheer number of combinations, and the preponderance of combinations that are observed with very low frequencies, precludes full information optimization of the kind used in models of policing behavior (e.g., Knowles *et al.* (2001)). The key source of ambiguity we explore in the numerical application is the fact that many country-product-firm combinations are observed very rarely.

In order to emphasize the role of ambiguity, we shut down by assumption other possible sources of cross-bin variation that might otherwise affect search behavior and/or compliance. We restrict the optimism parameter to be equal across bins, $\alpha_l = \alpha$, $\forall l$. Likewise the firm's loss parameter, L, is assumed to be common across bins.

We also parameterize the model in a such a way that

$$1 - \alpha > 1 - p(s_l^*) + (1 - s_l^*)p'(s_l^*), \tag{15}$$

which ensures that bins with greater ambiguity will be searched more intensively in equilibrium (see condition (9)). We choose $\alpha = 0.01$, a parametrization that implies a high degree of pessimism on the part of border officials.

The parameter L represents the loss to the firm from having non-compliant goods seized by the border authority. This parameter can be important in determining overall levels of compliance, and our model fits best with generally high levels of compliance. In our exercise we set $L = 10$.[37] We also choose the Pareto distribution scale parameter to generate relatively high levels of aggregate compliance; $b = 0.01$.

[37] The right-hand side of inequality (15) is decreasing in both s_l and L (recall $p(s_l) \equiv F(s_l L)$). With the relatively low levels of search activity observed in Serbian Customs (which results in low levels of search intensity), we need a high level of L for the calibration to satisfy inequality (15). In other words, we need to have high levels of compliance with low levels of search activity, which can be achieved with a hefty non-compliance cost.

Our key calibration target is the allocation of search activity across the seven shipment frequency bins. The structural parameters that determine these outcomes are the bin level ambiguity parameters δ_l. To calibrate these parameters we specify a parsimonious functional relationship between δ_l and $\bar{N}_{l,t-1}$, the mean lagged shipment frequency for that bin in the 2016 Serbian data. Our functional representation is

$$\delta_l = \frac{\gamma}{1 + \bar{N}_{l,t-1}}, \tag{16}$$

where γ is a calibration parameter.[38]

6.4 Equilibrium solution in the benchmark

The primary targets in our calibration exercise are the inspection rates that were observed for each bin, which we reported in Table 4 and reproduce in the first row of Table 5. In our calibration each bin has the same share of overall shipments as was reported in Table 4. We also impose the same aggregate search rate as was reported there, 7.3 inspections per 100 shipments. Given these restrictions and the parameter choices discussed in the previous subsection, we choose the value of γ in (16) to best match the inspection rate targets.

A value of $\gamma = 0.285$ aligns the inspection rates across bins reasonably well. The bins with lagged shipment frequencies of 0, 11-100 and 100+ account for more than 75 percent of all shipments, and the calibrated model matches inspection rates for these bins quite closely. The calibrated inspection rates for bins with 1 and 2 lagged shipments are furthest from the data, but the differences from observed inspection rates in the two bins are offsetting in terms of sign and magnitude. In broad terms the inspection rate falls with inspection frequency in much the same manner that is observed in the data.

The structural parameters that drive this variation are the δ_l's, all seven of which are pinned down by γ and equation (16). Table 5 reveals values of δ_l that drop rapidly across shipment frequency bins. The ambiguity level for shipments that were not observed in the prior year is nearly an order of magnitude higher than the level observed for shipments

[38] We experimented with other linear and simple non-linear functional forms, and found that (16) performed best.

Table 5: Benchmark Model Calibration

Lagged shipment frequency bin	0	1	2	3-5	6-10	11-100	100+
Inspections per 100 shipments (target)	14.6	6.7	6.7	6.2	5.9	5.8	5.6
Inspections per 100 shipments (fitted)	14.5	7.0	6.4	6.0	5.8	5.7	5.6
Ambiguity (δ_l)	0.285	0.143	0.095	0.059	0.033	0.010	0.001
Compliance rate per bin $p(s_l^*)$	0.993	0.986	0.984	0.983	0.983	0.982	0.982
Aggregate compliance rate p_{tot}				0.985			
Total inspections per 100 shipments				7.3			

Notes: The table reports key outcomes in the calibrated model. Data are organized by the lagged shipment frequency bins previously outlined. The first row reports inspections per 100 shipments for each bin in the 2016 data from Serbian customs. The second row reports the same figures in the model. Row three reports calibrated ambiguity parameters for each bin. Row four the compliance rate in each bin. Row five reports aggregate compliance in the calibrated model. Row six reports the aggregate inspection rate, which is taken from the 2016 data and replicated in the calibrated model.

occurring 6-10 times, and more than two orders of magnitude larger than the value of δ that applies to the bin with shipments observed more than 100 times in the prior year.

Since we have parameterized the model to produce equal probabilities of compliance across bins – conditional on equal search rates – observed variation in inspection rates is solely an outcome of cross-bin variation in δ_l. Given our objective function for the agency, one function of search is to mitigate the losses in the objective function that are linked to ambiguity. From the point of view of maximizing aggregate compliance, responding to ambiguity generates a misallocation of search activity. Firms respond to the variation in search intensity with different compliance rates. Compliance rates vary from 0.993 to 0.982. In aggregate, the compliance level in the benchmark is 0.985.[39]

6.5 Counterfactual analysis: a reverse reform scenario

Since our benchmark model represents a post-reform equilibrium, our counterfactual analysis represents the *reversal* of a risk management reform. A reform episode evaluated with

[39] We have no direct data on compliance levels in Serbian customs. This is a model outcome. The World Bank working paper version of Fernandes *et al.* (*forthcoming*) reports information on penalties assessed by Albanian customs in 2007, and finds that penalties were assessed on only 132 of 178,639 shipments, or 7/100ths of one percent. We choose not to calibrate to so high a compliance figure, but simply note that the high levels of compliance produced by our model are within a reasonable range.

Table 6: Removing IT a threefold increase in δ_l

Lagged shipment frequency bin	0	1	2	3-5	6-10	11-100	100+
δ_l	0.855	0.428	0.285	0.178	0.099	0.030	0.004
Inspections per 100 shipments	26.0	3.6	3.6	3.5	3.5	3.4	3.4
Compliance rate per bin $p(s_l^*)$	0.991	0.959	0.959	0.959	0.959	0.959	0.959
Aggregate compliance rate				0.975			
Total inspections per 100 shipments				7.3			

Notes: Results from a simulation that increased δ_l's by a factor of three from their benchmark levels. The first row reports the higher values of ambiguity in this simulation. The second row reports inspection rates across bin. Row three reports compliance rates at the bin level. Row four reports aggregate rates of compliance. Row five reports the number of total inspections per 100 shipments in the simulation, which remains at its benchmark level.

our model would typically involve a reduction of ambiguity (including the introduction of an IT system) paired with a reduction of aggregate search intensity. In this case we simulate an *increase* in ambiguity, which leads to a misallocation of search activity and lower rates of compliance, which in turn requires increased search activity to bring compliance rates back to benchmark levels. We conduct our counterfactual simulation in two parts: a sizable increase in ambiguity, followed by an increase in aggregate search.

6.5.1 Removing IT: the effects of increased ambiguity

In this subsection we consider the effects of increased ambiguity on search and compliance. Our counterfactual experiment is a tripling of δ_l in each bin. We report the counterfactual values of δ_l in the first row of Table 6. We choose a multiple of three to put the ambiguity level in the bin with zero lagged shipments in the neighborhood of 1. Its counterfactual value, 0.855, implies that the agency is very uncertain about the probabilities of compliance in this bin, but not fully uninformed. The proportional increase in ambiguity affects all bins, but has less bite among the more frequently observed shipments because benchmark levels of ambiguity are so low. Our rationale for proportional increases in δ_l is that inspecting agencies that lack sophisticated IT equipment should still be able to come to reasonable beliefs about compliance probabilities for shipments they observe frequently.

At this stage we have not allowed the agency to respond to higher levels of ambiguity with increased levels of search. As the second row of Table 6 indicates, the agency's response to increased ambiguity is to reallocate search even more heavily towards infrequently-observed shipments. In this scenario, search intensity nearly doubles for shipments that were not observed in the previous year. Increased search in the first bin is accomplished by reducing search intensity across all other bins.

Changes in search intensity are the channel through which the increase in ambiguity affects compliance rates across bins. In the one bin where search activity increases, firms respond by increasing compliance. In the other bins search falls and compliance falls. The net effect of the reallocation of search activity is to reduce aggregate compliance, which falls from 0.985 in the benchmark to 0.975 in this scenario.

We do not produce a quantitative estimate of the welfare costs of increased ambiguity, because we lack direct evidence on a key parameter, the social harm from non-compliant goods that enter the country. Given a measure of the social loss per shipment, calculating the welfare loss at this stage would be straightforward. The one percentage point reduction in aggregate compliance should be multiplied by the total number of import shipments, and by the social loss per non-compliant shipment.[40]

6.5.2 Compensating with increased aggregate search

A central question regarding prospective risk management reforms is the degree to which the improved targeting of search improves enforcement, and thus enables a reduction in total search activity. We address this question here by asking: how much additional search is necessary to generate equivalent levels of aggregate compliance as was observed in the benchmark calibration? To make this calculation, we follow an iterative procedure in which we increase gradually the aggregate search measure $\bar{S}$, and resolve the model. We iterate until the aggregate compliance rate equals that which was observed in the benchmark equilibrium $p_{tot} = 0.985$.

[40] In the model trade flows are exogenous, so there is no welfare loss and/or gain in the model from changes in trade flows. In this case there are no net changes in search activity, simply shifts of search intensity across bins. It is difficult to know how the elasticity of trade to search might vary across shipment frequency bins.

Table 7: Compensating with increased total search

Lagged shipment frequency bin	0	1	2	3-5	6-10	11-100	100+
Inspections per 100 shipments	100	100	7.3	5.9	5.3	5.0	4.9
Compliance rate (per bin) $p(s_l^*)$	0.999	0.999	0.986	0.983	0.981	0.980	0.980
Aggregate compliance rate				0.985			
Total inspections per 100 shipments				25.8			

Notes: The table shows equilibrium values for a scenario in which search intensity has increased to a level that is sufficient to return the total compliance rate to its benchmark level, 0.985. The table reports inspection and compliance rates per bin, the target compliance rate, and the aggregate search intensity needed to achieve this level of compliance.

The results of this exercise are reported in Table 7. The number of searches required to replicate benchmark compliance levels is more than 3 times as large as in the benchmark calibration (25.8 vs. 7.3). To hold compliance rates fixed, a tripling of ambiguity requires a 253 percent increase in total searches of import shipments. Conversely, the model suggests that a reform that reduces ambiguity by 66.7 percent can reduce overall search intensity by 71.7 percent without affecting compliance.[41]

One of the lessons of Table 7 is that the misallocation of search intensity persists (and is magnified) at higher levels of total search. Given more capacity to search, the agency chooses to search 100 percent of the shipments in the first two shipment frequency bins. The search intensity in the bins that see the most frequent shipments is even lower than in the benchmark. The firms in each bin respond accordingly with changed levels of compliance.

Because the increased search intensity has restored levels of aggregate compliance, the nature of the welfare loss due to reduced ambiguity takes a different form than that discussed in the previous section. In this case, the first order loss can be calculated as the parameter that represents the cost of conducting a search multiplied by the change in search intensity ($0.258 - 0.073 = 0.185$) multiplied by the total number of import shipments. We lack direct evidence on the size of search cost per shipment, yet assuming that the cost of search is 1% of the value of the goods, then the welfare cost of increased ambiguity is a tariff-equivalent

[41] Reductions in search intensity of this magnitude have been observed in the literature. The risk management reform in Albania studied by Fernandes *et al.* (*forthcoming*) saw the intensity of 'red channel' searches fall from 42.9 percent in 2007 to 11.2 percent in 2012.

trade cost of 0.185 percentage points.[42] It is also likely that increased search would reduce trade volumes, causing additional welfare losses. These effects jointly represent the benefits of risk management reforms. The costs of reform are primarily related to the purchase and operation of the IT system, as well as the retraining of the agency staff to work under the new protocols.

7 Conclusion

An ideal trade facilitation reform should accomplish two objectives that might otherwise seem to be in conflict. The reform should decrease the overall oversight burden on trading firms, while at the same time improving upon – or at least maintaining – existing levels of compliance. We have demonstrated how risk management reforms that include the adoption of modern IT systems might jointly achieve both objectives. We argue that a fundamental problem in the oversight of imported goods shipments is that the enormous variety of products, countries of origin, trading firms and compliance risks makes it extremely difficult for oversight agencies to make an informed assessment of the *ex ante* probability that a given shipment is a non-compliance risk. This ambiguity about expected probabilities of non-compliance often means that developing country border management agencies conduct too many inspections, and do a poor job of targeting inspections. Modern IT systems are instrumental in reducing this ambiguity, and are thus a critical component of the trade facilitation reform known as risk management.

In order to demonstrate these insights formally, we develop a tractable form of a Choquet Expected Utility framework that formalizes ambiguity in terms of a single parameter. Under our assumed objective function, search plays two roles: discouraging non-compliant behavior, and reducing ambiguity in cases when the inspecting agency is pessimistic about compliance. We offer circumstantial empirical evidence from Serbia suggesting that ambiguity matters for search – even when sophisticated IT systems are already in place. The evidence that

[42] Note that in contrast to a tariff, this trade cost generates no tax revenue. Additional search imposes real resource costs, so the welfare loss is significantly larger than from an equivalent tariff that raises revenue.

ambiguity matters suggests that the second motive in our objective function is relevant: inspecting agencies mitigate ambiguity with additional search. We develop a quantitative model to illustrate, numerically, the role of ambiguity in a realistic parameterization of the distribution of search activity and firm-level compliance. Our results are indicative of the kinds of benefits that accrue to countries that successfully implement risk management.

Our purpose in this paper is to demonstrate the relevance of ambiguity as a challenge for targeting border inspections. Specifically we wish to isolate the channels through which risk management reforms involving modern IT achieve key trade facilitation goals. It is difficult to conceive of a direct measure of ambiguity, and our empirical work is therefore suggestive, rather than conclusive, about the importance of ambiguity. Confidentiality issues mean that we also lack an important omitted variable – past rates of non-compliance. Customs agencies would have this information and use it to improve their inspection decisions.

Our numerical simulation is designed to illustrate the quantitative implications of IT-based reforms that reduce ambiguity. High levels of ambiguity lead to misallocation of search activity, which means that higher total search intensities are necessary to hold compliance fixed. Reforms that successfully integrate IT can facilitate trade through reduced search, even while maintaining aggregate rates of compliance.

Appendix

General Framework

It is assumed that the uncertainty that inspection agency faces can be described by a non-empty finite set of states, Γ. There is a set of events, ϵ, associated with the set of states, which are the power set of Γ. It is assumed that for each γ in Γ, $\{\gamma\}$ is in ϵ. Let $X \subset \mathbb{R}$ be a non-empty, finite set of outcomes and let $G = \{g : \Gamma \to X\}$ be a simple set of functions from states to outcomes, called simple acts. Let $U : X \to \mathbb{R}$ be a monotone increasing function from outcomes to real numbers.

Definition of Capacity. A capacity is a function $\mu : \epsilon \to \mathbb{R}$ which assigns real numbers to events such that (i) D, $E \in \epsilon$ and $D \subseteq E$ implies $\mu(D) \leq \mu(E)$ (monotonicity), and (ii) $\mu(\varnothing) = 0$ and $\mu(\Gamma) = 1$ (normalization).

Note that a probability distribution is a special case of a capacity that satisfies additivity: D, $E \in \epsilon$ and $D \cap E = \varnothing$ implies $\mu(D) + \mu(E) = \mu(D \cup E)$.

Definition of Choquet Integral. Let $g : \Gamma \to X$ be a simple act that takes on the values $x_1 \geqslant x_2 \geqslant ... \geqslant x_n$. The Choquet integral of g with respect to a capacity μ is defined as

$$\int g d\mu := \sum_{i=1}^{n} x_i.[\mu(\{\gamma \in \Gamma \mid g(\gamma) \geqslant x_i\}) - \mu(\{\gamma \in \Gamma \mid g(\gamma) > x_i\})].$$

The Choquet integral can be interpreted as the expected value of the simple act g with respect to the capacity μ. The Choquet integral of the composition $U(g(\gamma))$ with respect to the capacity μ is defined as the Choquet Expected Utility of g with respect to μ. Note that the composition $U(g(\gamma)) : \Gamma \to \mathbb{R}$ is a simple act.

A neo-additive capacity is a special type of capacity that is based on a probability distribution.

Definition of Neo-additive Capacity. Let α and δ be real numbers such that $0 \leq \delta \leq 1$ and $0 \leq \alpha \leq 1$. A neo-additive capacity v based on a probability distribution π is defined as

$$v(D) := \begin{cases} 0 & \text{for } D = \varnothing \\ \delta\alpha + (1-\delta)\pi(D) & \text{for } \varnothing \subsetneq D \subsetneq \Gamma \\ 1 & \text{for } D = \Gamma. \end{cases}$$

A neo-additive capacity is additive on non-extreme outcomes. Here, π represents the agent's beliefs about the likelihood of uncertain events, and $1 - \delta$ represents the agent's degree of confidence in this belief. The complement of the degree of confidence is the degree of ambiguity δ.

The Choquet integral of a simple act g with respect to a neo-additive capacity v based on π is given by (see Chateauneuf, Eichberger and Grant, 2007)

$$\int g dv = \delta\alpha x_1 + \delta(1-\alpha)x_n + (1-\delta)\sum_{i=1}^{n} x_i.\pi(\{\gamma \in \Gamma \mid g(\gamma) = x_i\}),$$

where g takes on the values $x_1 \geqslant x_2 \geqslant ... \geqslant x_n$. Therefore, with respect to a neo-additive capacity, the Choquet integral of a simple act g is the weighted sum of the best outcome under g, the worst outcome under g, and the expected value of g with respect to π.

It follows that the Choquet Expected Utility of the simple act g with respect to the neo-additive capacity v based on π is given by

$$V_\pi(g) := \int U(g)dv = \delta\alpha U(x_1) + \delta(1-\alpha)U(x_n) + (1-\delta)E_\pi(g),$$

where $E_\pi(g) \equiv \sum_{i=1}^{n} U(x_i).\pi(\{\gamma \in \Gamma \mid U(g(\gamma)) = U(x_i)\})$. That is, it is the weighted sum of the maximum utility under g, the minimum utility under g, and the expected utility of g with respect to π. In the above integral, α can be interpreted as the degree of optimism and $1-\alpha$ as the degree of pessimism since they are weights given to the maximum and the minimum utility, respectively. Notice when no ambiguity exists, the Choquet Expected Utility reduces to expected utility.

The Current Model

The state space is Γ =\{compliance, no compliance\}. The outcome space is $X_l = \{M(s_l), m(s_l)\}$, where $M(s_l) = 0$ and $m(s_l) = N_l\,(1-s_l)$. The set of acts $G = \{g(s_l) : s_l \geqslant 0\}$, where

$$g(s_l) = \begin{cases} M(s_l) & \text{if } \gamma = \text{compliance} \\ m(s_l) & \text{if } \gamma = \text{no compliance.} \end{cases}$$

The inspecting agency's utility function is $U(g(s_l)) = g(s_l)$.

The inspecting agency's beliefs about the HSE risk are given by a neo-additive capacity based on the probability distribution $\pi_l = \{p_l(s_l), 1-p_l(s_l)\}$. Define $v(p) := v(\text{compliance})$, $v(1-p) := v(\text{no compliance})$, and $V_{p_l}(s_l) := V_{p_l}(g(s_l))$. Moreover, define $E_{p_l}(s_l) := p_l(s_l)M(s_l) + (1-p_l(s_l))m(s_l)$. It follows that the inspecting agency's Choquet Expected Utility of searching a random good from group l with intensity s_l is $V_{p_l}(s_l) = \delta_l\alpha_l M(s_l) + \delta_l(1-\alpha_l)m(s_l) + (1-\delta_l)E_{p_l}(s_l)$.

References

[1] Armenter, R. and M. Koren, 2014. A balls-and-bins model of trade. *American Economic Review* 104(7), pp. 2127–2151.

[2] Bigus, J., 2012. Vague auditing standards and ambiguity aversion. *Auditing: A Journal of Practice & Theory* 31(3), pp. 23-45.

[3] Camerer, C., 1995. Individual decision making. In: John H. Hagel and Alvin E. Roth (eds.), *The Handbook of Experimental Economics*. Princeton, New Jersey: Princeton University Press, pp. 587-703.

[4] Cariolle, J., C. Chalendard, A.-M. Geourjon and B. Laporte, 2019. Measuring and improving the performance of customs valuation controls: an illustration with Gabon. *World Economy* 42(6), pp. 1850-1872.

[5] Chalendard, C., G. Raballand and A. Rakotoarisoa, 2019. The use of detailed statistical data in customs reforms: the case of Madagascar. *Development Policy Review* 37(4), pp. 546-563.

[6] Chateauneuf, A., J. Eichberger and S. Grant, 2007. Choice under uncertainty with the best and worst in mind: neo-additive capacities. *Journal of Economic Theory* 137(1), pp. 538-567.

[7] Eeckhout, J., N. Persico and P.E. Todd, 2010. A theory of optimal crackdowns. *American Economic Review* 100(3), pp. 1104-1135.

[8] Ellsberg, D., 1961. Risk, ambiguity and the Savage axioms. *Quarterly Journal of Economics* 75(4), pp. 643-669.

[9] Fernandes, A.M., R. Hillberry and A.M. Alcantara, *forthcoming*. Trade effects of customs reform: evidence from Albania. *World Bank Economic Review*.

[10] Fernandes, A.M., R. Hillberry and A.M. Alcantara, 2017. An evaluation of border management reforms in a technical agency. World Bank Policy Research Working Paper 8208, October.

[11] Knowles, J., N. Persico and P.E. Todd, 2001. Racial bias in motor vehicle searches: theory and evidence. *Journal of Political Economy* 109(1), pp. 203-229.

[12] Lazear, E.P., 2006. Speeding, terrorism, and teaching to the test. *Quarterly Journal of Economics* 121(3), pp. 1029-1061.

[13] Martincus, C.V., J. Carballo and A. Graziano, 2015. Customs. *Journal of International Economics* 96(1), pp. 119-137.

[14] Persico, N., 2002. Racial profiling, fairness, and effectiveness of policing. *American Economic Review* 92(5), pp. 1472-1497.

[15] Persico, N. and P.E. Todd, 2008. The hit rates test for racial bias in motor-vehicle searches. *Justice Quarterly* 25(1), pp. 37-53.

[16] Savage, L.J., 1954. *The Foundations of Statistics.* New York: Wiley.

[17] Schmeidler, D., 1989. Subjective probability and expected utility without additivity. *Econometrica* 57(3), pp. 571-587.

[18] Teitelbaum, J.C., 2007. A unilateral accident model under ambiguity. *Journal of Legal Studies* 36(2), pp. 431–477.

[19] Widdowson, D. and S. Holloway, 2011. Chapter 6: Core border management disciplines: risk based compliance management. In: Gerard McLinden, Enrique Fanta, David Widdowson and Tom Doyle (eds.), *Border Managament Modernization.* The World Bank, Washington, D.C., pp. 95-113.