Policy Research Working Paper 9802

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WORLD BANK GROUP
Development Economics
Development Research Group
&
Governance Global Practice
October 2021

Policy Research Working Paper 9802

Abstract

This paper presents a new methodology to detect corruption in customs and applies it to Madagascar's main port. Manipulation of assignment of import declarations to inspectors is identified by measuring deviations from random assignment prescribed by official rules. Deviant declarations are more at risk of tax evasion, yet less likely to be deemed fraudulent by inspectors, who also clear them faster. An intervention in which inspector assignment was delegated to a third party validates the approach, but also triggered a novel manifestation of manipulation that rejuvenated systemic corruption. Tax revenue losses associated with the corruption scheme are approximately 3 percent of total taxes collected and highly concentrated among a select few inspectors and brokers.

This paper is a product of the Development Research Group, Development Economics and the Governance Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at cchalendard@intracen.org, afernandes@worldbank.org, graballand@worldbank.org, and brijkers@worldbank.org.

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Originally published in the Policy Research Working Paper Series on *October 2021*. This version is updated on *August 2022*.
To obtain the originally published version, please email prwp@worldbank.org.

Key words: corruption, tax enforcement, tariff evasion, trade policy

JEL codes: F13, D73, H26

‡ International Trade Centre, † Development Research Group, World Bank, § Governance Global Practice, World Bank, and Université Clermont Auvergne, CNRS, CERDI, F63000 Clermont-Ferrand, ∓ Development Research Group, World Bank, and Utrecht School of Economics, Utrecht University. We thank the editor and five referees for excellent comments that greatly improved the paper. We thank Madagascar Customs and GasyNet for sharing their data, feedback, and willingness to collaborate. We are especially grateful to former director general Éric Rabenja who courageously implemented a host of anti-corruption reforms, at high personal cost. The support of Dannick Fiononana, Antsa Rakotoarisoa, Cédric Catheline, Stéphane Manouvrier, Prisca Michea, Tolotra Hasinantenaina Ramarosandratana, and Tahina Rabesalama, was critical to the success of this project. We thank Paula Irene Londono Suarez, Nicolas Santos, and Tomas Rossetti for superb research assistance. Aaditya Mattoo provided extremely useful comments and guidance, especially in the early stages of the project. We also thank Thomas Cantens, Vianney Dequiedt, Simeon Djankov, Henrik Kleven, Beata Javorcik, Joana Naritomi, Tristan Reed, Sandra Sequeira, Joana Silva, Joel Slemrod, René Tapsoba, Roy van der Weide, Shang-Jin Wei, and seminar/conference participants at the 2018 ABCDE conference, the 2021 Canadian Economic Association Annual Meeting, CESIfo, FREIT and Georgia Institute of Technology Empirical Trade Online Seminar 2020, NUS, the Tinbergen Institute, UNU-WIDER, the 2018 Midwest Economic Theory and International Trade Conference, the 2020 NBER Development Economics Program Meeting, the World Bank, and the 2017 World Customs Organization PICARD Conference, for useful comments and discussions. This paper has been partly supported by the Umbrella Facility for Trade trust fund (financed by the governments of the Netherlands, Norway, Sweden, Switzerland and the United Kingdom) and the Strategic Research Partnership on Economic Development. We also acknowledge the generous financial support from the World Bank research support budget and the Knowledge for Change Program (KCP), a trust funded partnership in support of research and data collection on poverty reduction and sustainable development housed in the office of the Chief Economist of the World Bank. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank of Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the countries they represent. The views expressed herein are those of the authors and do not necessarily reflect the views of the International Trade Centre and the United Nations. All errors are our responsibility. The authors can be contacted at cchalendard@intracen.org, afernandes@worlbank.org, graballand@worldbank.org and brijkers@worldbank.org (corresponding author).

1 Introduction

State capacity to raise tax revenue is an important enabler of development (Besley and Persson, 2009). Poorer countries mobilize less tax revenue as a share of GDP (Gordon and Li, 2009) and suffer higher levels of corruption. While tax evasion and weak bureaucratic performance are salient drivers of the differences in revenue mobilization across the development spectrum (Finan et al., 2017, Khan et al., 2015, Khan et al., 2019), less is known about who evades (how much), and to what extent evasion is facilitated by (which) bureaucrats. Evidence on the effectiveness of reforms to remedy systemic corruption is also scant.

This paper presents a new methodology to detect and quantify the prevalence and costs of a type of corruption scheme in customs, and assesses the effectiveness of an intervention intended to eliminate such corruption. Across the globe, customs information technology (IT) systems usually prescribe random assignment of incoming declarations to inspectors, conditional on their productivity (in the task of clearing declarations), as a way to deter corruption. Our approach identifies potential manipulation of inspector assignment by evaluating whether certain inspectors are paired excessively frequently with certain customs brokers, deviating from what conditional random assignment would predict. To assess whether these deviations reflect corruption, we subsequently examine whether excess interaction between inspectors and brokers is associated with an increased risk of tax evasion and whether deviant declarations are treated preferentially by inspectors. We quantify the resulting tax revenue losses and their distribution across inspectors and brokers. The methodology is validated by studying the impact of an intervention that delegates the (randomization of) inspector assignment to a third party organization external to customs.

We apply our approach to Madagascar's main port, Toamasina, which provides a suitable setting for studying corruption in customs. First, like many other developing countries, Madagascar is heavily reliant on tax revenues collected at the border (Baunsgaard and Keen, 2010), which account for 48 percent of total tax revenues. Toamasina collects more than three quarters (78 percent) of non-oil tax revenues and employs a limited number of inspectors. Each inspector oversees the collection of 1.3 percent of total yearly taxes in Madagascar. Second, corruption appears rife in customs. A survey of inspectors reveals that only 6 percent believe non-ethical conduct is sanctioned, and only 23 percent believe their colleagues act with integrity. Third, inspectors repeatedly interact with a limited number of brokers, with whom they also share social ties. The combination of high stakes, a small number of players, limited sanctions for improper conduct and extensive repeated interactions is conducive to corruption. Last but not least, Madagascar's senior customs management were willing to undertake reforms to curb corruption and provided us unprecedented data access. They shared data for the period 2015-2018 covering rich details on each import declaration including declared value and weight, weight measured upon arrival at the port, taxes paid, the identity of the broker which registered it and the inspector assigned to it, whether fraud was recorded, all revisions to inspector assignment, value, weight, and tax liability made during the clearance process, as well as risk management information (inspection channel, risk scores, and valuation advice).

Our methodology comprises three steps. First, we detect potential manipulation of inspector assignment by identifying pairings of inspectors with brokers that occur much more frequently than would be expected on the basis of conditional random assignment. In Toamasina, 10 percent of all declarations are handled by inspectors whose assignment contravened the random inspector assignment prescribed by official rules. Second, these deviant declarations are shown to have characteristics commonly associated with an elevated risk of tariff evasion and to embody sizeable potential tax revenue losses. Third, we demonstrate that inspectors treat preferentially the declarations registered by brokers with whom they interact excessively frequently ceteris paribus. They clear them faster, are less likely to deem them fraudulent, and impose lower weight, value and tax adjustments, thus exacerbating disparities in tax revenue losses between deviant and non-deviant declarations. These findings are robust to a variety of checks, including the use of inspector-specific binomial logit models to detect deviations from random assignment whilst accounting for fluctuations in inspectors' schedules, using a propensity score matching approach to account for selection, using different samples and controlling for various sets of fixed effects. According to back-of-the-envelope calculations, average tax revenue per non-randomly assigned declaration would have been 26 percent higher in the absence of excess interaction. Total tax revenues collected in Toamasina would have been 3 percent higher.[1]

We argue that these patterns are consistent with a corruption scheme in which brokers bribe staff in the customs information technology (IT) department and/or the customs port manager to be paired with their preferred inspector, who agrees to clear the declarations that are the object of corruption faster, not to impose tax adjustments and penalties, not to insist on upward adjustment (or to request just a marginal one) of the customs declared value. The resulting tax savings are presumably shared with inspectors. Although we do not directly observe bribe payments, our findings are consistent with extensive circumstantial evidence collected during repeated field visits, IT audits, and a survey of customs inspectors. Based on our findings, Madagascar's customs management sanctioned inspectors for corruption, suspended the head of the IT department and reformed inspector assignment by divesting it to a third party outside customs. This delegated randomization made the third party responsible for inspector assignment. Using its own software the third party randomly assigned declarations. It was so successful in eliminating deviations from random inspector assignment that delegated randomization became standard practice.

Explanations other than corruption are difficult to reconcile with the totality of the observed patterns. They also fail to explain why the delegated randomization intervention virtually eliminated the prevalence of deviations from random inspector assignment. IT manipulation resurfaced after a few months, however, albeit in a different guise. Customs IT staff figured out a new way to manipulate inspector assignment

[1]As discussed in Section 4, our approach does not capture all forms of corruption, hence these estimated losses reflect only the tax revenue losses associated with the specific corruption scheme we document.

and bypass the delegated randomization. This bypassing was identified by assessing whether the entire set of declarations registered by brokers was shared with the third party for inspector random assignment. We show that 7.2 percent of all import declarations were withheld from delegated randomization.[2] The circumvention of the delegated randomization not only attests to the difficulties inherent in the dislodging systemic corruption but also provides variation in exposure to the delegated randomization intervention.

The bypassing resulted in the resurgence of excess interaction between inspectors and brokers, driven exclusively by withheld declarations.[3] Interestingly, withheld declarations were disproportionately assigned to inspectors with whom brokers had interacted excessively frequently in the period before the delegated randomization intervention, suggesting persistence in the corruption scheme we unveil. These withheld declarations were on average more risky, subject to higher taxes, more undervalued, and embodied larger tax revenue losses, especially when their eventual (non-random) assignment resulted in excess interaction between inspectors and brokers. Inspectors only provided preferential treatment to withheld declarations if registered by brokers with whom they interact excessively frequently. These findings validate our methodology and are consistent with our interpretation that the documented patterns reflect corruption.

Our paper builds on, and aims to contribute to, several strands of literature. First, by presenting a methodology that can help detect tampering with random assignment, we aim to contribute to the literature on the detection and measurement of corruption and its development consequences (Bardhan 1997; Olken and Pande 2012; Shleifer and Vishny 1993; Shleifer and Vishny 2002; Zitzewitz 2012). Random assignment of declarations to inspectors is not only the norm in customs agencies across the globe, but is also used to prevent corruption in a plethora of other settings including the assignment of cases to judges and prosecutors.[4] We believe our approach can fruitfully be adapted to other contexts.

Second, we contribute to the nascent literature on the performance of bureaucrats as a determinant of state effectiveness and tax collection (Olken and Pande 2012; Dincecco and Ravanilla 2017; Pepinsky et al. 2017; Xu 2018; Xu et al. 2018), by highlighting the granularity of tax evasion and showing how the behavior of a select few actors has macro-fiscal ramifications. While corruption was systemic and enabled by most inspectors (10 out of 16 in a typical semester), IT staff, and the port manager, the tax revenue losses were very concentrated among a select few inspectors and brokers. In any given semester the top 2 most corrupt inspectors accounted for 55 percent of the tax revenue losses associated with the corruption scheme we document.

Third and related, we contribute to the literature on the determinants of tax enforcement (Kleven et

[2]In practice, such bypassing appears to have been operationalized through the temporary disabling of a randomization trigger, such that all declarations registered during specific time intervals when this trigger was deactivated were withheld from being sent to the third party to be randomized (including those that were the subject of a corruption agreement).

[3]Excess interaction was not observed for declarations handled by inspectors whose assignment was randomized.

[4]More than 100 customs agencies have adopted the customs clearance IT system used by Madagascar (Automated System for Customs Data (ASYCUDA)) for which the default option for assignment of declarations to inspectors is random assignment (according to workload). Customs agencies that do not use ASYCUDA also typically use random inspector assignment. Random assignment of cases to judges to deter judicial corruption has been adopted by 162 countries (Doing Business, 2020).

al. 2011; Pomeranz and Vila Belda 2019; Slemrod 2019), and specifically the literature on tariff evasion (Bhagwati 1964; Fisman and Wei 2004; Yang 2008a; Yang 2008b; Dutt and Traca 2010; Sequeira and Djankov 2014; Sequeira 2016; Rijkers et al. 2017; Wier 2020) by pinpointing which brokers and inspectors cheat, and which import declarations are most likely to be undervalued. The propensity to participate in the corruption scheme is higher for brokers based in Toamasina and rises with inspectors' tenure in the port, suggesting that private information and personal relationships are important enablers of evasion. Despite accounting for larger tax revenue losses the most corrupt inspectors paradoxically collected more tax per declaration than less corrupt ones because manipulation of assignment enabled them to control the assessment of the most lucrative declarations with the highest potential tax yield. Corruption is thus positively correlated with (naively measured) tax yield.

Fourth, our results also dovetail with the literature on the effectiveness of anti-corruption interventions (e.g., Ferraz and Finan 2008; Niehaus and Sukhtankar 2013) by demonstrating that IT solutions can help curb corruption (see also Lajaaj et al. 2019), but are not a panacea (see also Casaburi et al. 2019) because they can also serve as a conduit to it. Our evidence of a new form of IT manipulation after the reform to inspector assignment is consistent with Shleifer and Vishny's (1993) observation that corruption is difficult to dislodge when both parties benefit (as in corruption with theft). It also complements Yang (2008a) who shows how a customs reform that increased enforcement against a specific type of tariff duty evasion resulted in the use of an alternative duty-avoidance method (shipping via duty-exempt export processing zones).[5]

Finally, our findings are relevant for the understanding of trade costs, market distortions, and competition in developing countries (Atkin and Khandelwal 2019) and the debate as to whether corruption greases the wheels of the economy (e.g., Banerjee et al. 2012; Leff 1964; Kaufmann and Wei 1999; Freund et al., 2016). We complement Sequeira (2016)'s findings that in the presence of corruption, tariffs and other import taxes may not be as burdensome as they appear on paper by showing that corruption is also associated with faster clearance. Expedited clearance limits the risk of detection, and is another margin by which corruption impacts trade costs and competition.[6]

The remainder of this paper is organized as follows. Section 2 describes the context and the customs clearance process while Section 3 presents our data. Section 4 describes our methodology to detect deviations from official rules in inspector assignment to declarations. Section 5 examines whether deviant declarations are at a higher risk of tax evasion. Section 6 assesses whether there is differential treatment of deviant

[5] Our study's displacement is mediated by interactions between private sector parties (brokers) and bureaucrats (inspectors) and is thus close to Lichand and Fernandes (2019) who document selection in the pairing of vendors and bureaucrats in response to changes in (perceptions of) enforcement of anti-corruption measures.

[6] Note, however, that our results are not informative about the overall impact of corruption on clearance times. In theory, inspectors who participate in the scheme could attempt to extort non-participating firms by protracting the clearance process. In practice, however, clearance times are fairly short even for declarations that are not covered by the scheme - about 20 hours on average - so prima facie the data are not suggestive of substantial extortion.

declarations by inspectors. Section 7 provides estimates of the costs of corruption in terms of tax losses. Section 8 characterizes the inspectors and brokers who are corrupt and the distribution of tax revenue losses. Section 9 validates our approach by analyzing the impact of the delegated randomization intervention. Section 10 concludes.

2 Context: Customs Clearance Process in Madagascar

This section describes the customs clearance process and argues that the conditions in Toamasina are conducive to systemic corruption: there are few players who interact repeatedly, the stakes are high, and there is almost no punishment for improper conduct.

Taxes and duties collected by customs accounted for 48 percent of overall tax revenue in Madagascar in 2019, despite substantial tariff evasion (Chalendard et al., 2019). Most of this revenue was collected in Toamasina, which accounted for 78 percent of non-oil tax revenue and 52 percent of non-oil imports and employed on average 16 inspectors per year during our sample period. Each inspector oversees the collection of 17 million USD worth of tax revenue per year on average, representing 1.3 percent of total taxes collected.

Jobs in the customs administration - especially inspector jobs in Toamasina - are among the most sought-after jobs in Madagascar. They are secure, well-paid, and offer several benefits. Inspectors earn a salary of roughly 11,000 USD per year (21 times annual GDP per capita of 527 USD) and receive as bonus 5 to 20 percent of the tax adjustments they impose when they detect non-compliance.[7] They can also earn performance bonuses of up to 1,000 USD per quarter if they are among the top inspectors in terms of clearance speed, fraud detection, and tax revenue mobilization. Inspectors thus get paid efficiency wages and have strong personal financial incentives to detect non-compliance, which should help deter corruption.

However, these performance rewards may not sufficiently incentivize inspectors to act with integrity. Corruption appears pervasive, possibly due to the virtual absence of sanctions for improper conduct, threats from economic operators, and because compensation is low relative to opportunities for graft (Chalendard et al. 2020). According to a nationwide survey of inspectors that we conducted in 2017, only 23 percent believe that their colleagues act with integrity, only 6 percent claim non-ethical behavior is sanctioned and only 12 percent believe promotions are merit-based. Close to a third of inspectors claim being subjected to threats from economic operators on a regular basis. Undervaluation of imports was widely agreed to be the main type of customs fraud in Madagascar.[8]

The inspectors in Toamasina interact with a limited number of customs brokers (*commissionnaires agrées*

[7]Note that inspectors' pay does not vary mechanically with the total taxes they collect.

[8]Administrative data on fraud records classify 67.2 percent of all fraud in Madagascar customs as underreporting of value, 27.4 percent as underreporting of quantities, and the remainder as product misclassification (4.9 percent) or misreporting country of origin (0.5 percent).

en douane). In a typical semester, there are on average 45 brokers who each handle 173 declarations from 33 different importers.[9] The overwhelming majority of the 3,660 importers in our sample work exclusively with one broker, as is shown in Appendix Table A2. Brokers must have a license, which is issued by the customs administration and they administer the customs clearance process on behalf of the importer by fulfilling customs formalities and submitting documentation.[10] Brokers are accountable for the payment of taxes, duties and potential tax adjustments and are penalized (with a fine) in case of non-compliance. In principle, repeated non-compliance can result in the revocation of the broker's license. In practice, suspension of brokers due to misconduct is rare. Customs officials and brokers frequently socialize and are part of the narrow elite in the small town of Toamasina. Many brokers either have served as customs officials themselves, or deliberately recruit former customs officials because of their expertise and networks. Thus, there is extensive repeated interaction between inspectors and brokers, both inside and outside of the customs premises.

There is significant information asymmetry between importers and brokers given that the latter are much better informed about customs procedures and are the first point of contact for customs in case disputes arise. Some brokers have transparent pricing schemes which typically depend on the size and contents of the cargo, but others charge a fixed amount (inclusive of potential tax liabilities) per container cleared, irrespective of its content, which implies that their profits directly depend on the amount of tax they remit on behalf of the importer.

To understand how corruption may happen it is instructive to consider the customs clearance process, a stylized version of which is depicted in Figure 1.

1. **Registration.** The first step in the process is the electronic registration of an import declaration by the broker on behalf of the importer via the Automated System for Customs Data (ASYCUDA)++ customs clearance IT system.[11]

2. **Risk analysis.** The second step consists in risk analysis conducted by both GasyNet, a third party service provider that assists Madagascar customs with risk analysis and logistics, and the customs risk management unit.[12] For each declaration, (i) a risk score is issued based on GasyNet's proprietary risk model, (ii) a clearance channel is recommended along with a qualitative justification. If the yellow channel is selected the inspector only needs to check the documentation. If the red channel is selected the inspector is expected to physically inspect the cargo. However, the inspector is at liberty to change the clearance channel based on her own judgment. In addition, (iii) for a very small subset

[9] These averages do not consider small brokers (i.e., those handling less than 50 declarations per semester) since they will not be part of our estimating sample (described in Section 3).

[10] A very small number of importers - 6 in our sample - obtained their own broker's license and simultaneously act as importer and broker. They handle 3.2 percent of the declarations.

[11] ASYCUDA is an integrated customs management system developed by United Nations Conference on Trade and Development (UNCTAD) that has been adopted by more than 100 countries' customs agencies.

[12] In reality the second step (risk analysis) and the third step (inspector assignment) happen simultaneously.

of high-risk declarations for which the accuracy of the declared import value is questionable, GasyNet issues a valuation advice: a detailed report on what the value of the specific declaration is likely to be.

3. **Inspector assignment.** The third, and for our purposes, crucial step is the assignment of the declaration to a particular inspector by the ASYCUDA IT system. Official rules prescribe that a newly registered declaration should be assigned to whichever inspector has the lowest workload (i.e., has the fewest pending declarations on his/her desk) and is active (i.e., is connected to the IT system and can therefore receive new declarations). Official rules do allow for productivity differences across inspectors: a highly productive inspector will get, on average, more declarations than a poorly productive inspector. Yet, the assignment of declarations to inspectors is supposed to be random conditional on her/his productivity. We will exploit this feature of the official rules for identifying deviant declarations in Section 4.

   However, the customs port manager, the *Chef des Opérations Commerciales* (COPCO), has the authority to override the IT system's initial assignment and re-assign a declaration to a different active inspector. Such re-assignments are warranted in case of unanticipated absenteeism (due to illness for example) and, should, *a priori*, happen only randomly.[13]

4. **Assessment.** The fourth step is the assessment of the declaration by the assigned inspector based on the documentation submitted by the broker on behalf of the importer, the risk analysis diagnostics provided by the risk management unit and GasyNet, and the results of a potential physical inspection. She has to decide which (if any) adjustments to the import value, quantity, product classification and/or origin are to be made and report whether fraud was perpetrated. She then assesses what duties, taxes and potential penalties are to be paid based on the (potentially revised) final value and product classification of the import declaration.

5. **Clearance.** In the final step in which goods are cleared, the importer (or the broker on behalf of the importer) pays the taxes, duties and potential penalties and goods are released from customs.

Our analysis of corruption will focus both on manipulation of the assignment of declarations to inspectors (by IT department staff and/or the customs port manager) done in step 3, and on differential treatment of manipulated declarations by inspectors during assessment in step 4.

3 Data

Our study combines the following databases.

[13]Such re-assignments occur for 6 percent of the import declarations.

- **Customs transactions data** From Madagascar customs we obtained administrative data tracking imports at the transaction level for the period January 2015-November 2018. For each import declaration, the data covers the HS 8-digit products included (designated as items), their source country, the dates/times of registration, assessment, and clearance, the broker, the importing firm, and, the customs inspector assigned to handle the declaration. For each item, the data contain information on both the initially declared and the finally registered import value, weight, and taxes paid (tariff and value added tax as well as exemptions). These variables enable us to evaluate inspector modifications of value, weight, and tax liabilities. In addition, for each declaration we can track any modifications made to the IT system's initial inspector assignment by the customs port manager.[14] This will allow us to disentangle the role of IT department staff from that of the customs port manager in generating deviations from official rules in inspector assignment.

- **Fraud records** Fraud records were provided by the Legal Department (*Service des Affaires Juridiques et du Contentieux*). For each declaration, we know both whether and if so what type(s) of fraud was detected and the amount of taxes recovered (if any). Information on whether and how much inspectors modified tax yield is important for assessing the role of inspectors.

- **Risk management data** From the customs risk management unit we received for each import declaration information on the initial and finally-used clearance channel (documentary control/yellow channel, physical inspection/red channel or no inspection/blue channel). From GasyNet we received the risk score assigned to each import declaration (related to the risk of non-compliance with customs regulations ranging from 1 to 9) and valuation advice in case it was issued.

- **Container weight measurement data** We obtained from the company in charge of managing Toamasina's container terminal - Madagascar International Container Terminal Services Limited (MICTSL) - data on the weight of containers that arrive in Toamasina as measured by weighing at a scale upon arrival for the period 2015-2017. This port authority weight data is merged to the customs data at the declaration level, for declarations whose goods fill completely one or more containers. For declarations that share containers with other declarations this information is missing. These port authority weight data provide a useful benchmark for verifying whether the weight registered by the broker is correct.

- **UN COMTRADE data** We rely on an international trade data source UN COMTRADE to obtain export flows - values and quantities (weight) - at the country-HS 6-digit-year level for all of Madagascar's trading partners in 2015-2018. We use this mirror data for flows imported by Madagascar

[14]This data was obtained from the customs administration's internal control systems and merged to the transaction data.

to construct exogenous benchmark/reference prices to which we will compare the unit prices of the items included the import declarations in the Madagascar customs data (as will be described below).

- **Delegated randomization of inspector assignment and IT manipulation** On November 18, 2017 the assignment of inspectors to declarations was delegated to GasyNet. By comparing daily their list of declarations (that their system randomly assigned to some inspector) to the list of declarations that cleared customs from the customs administration, GasyNet was able to identify declarations that were withheld from the delegated randomization - as will be discussed in Section 9. They provided us with the list of withheld declarations.

- **Human resources data** Information on inspectors' gender, education, age, and date of entry into work for the customs administration were provided by the Human Resources Department (*Direction des ressources et de la formation*).

- **Inspectors' survey** In 2017 we conducted a nationwide survey of inspectors which contained questions on job and pay satisfaction, corruption, ethics, fairness, and interactions with brokers and importers.

Madagascar's raw customs data covers all formal import transactions made under several regimes: final imports for consumption (imports for home use), re-imports, temporary admissions, inward processing, warehouse, and other. Our analysis focuses on import declarations subject to taxation and to a physical or a documentary control by customs inspectors in Toamasina.[15] This implies focusing only on imports for home use and re-imports and excluding declarations from importers that are members of the "*Procédure Accélérée de Dédouanement*" (PAD), a trusted trader program that allows member firms to benefit from expedited clearance procedures with minimal controls at the border. To minimize the risk of identifying as likely to be suspect of corruption declarations that are not, we remove from the sample (i) declarations registered by brokers that do not interact frequently with customs (i.e., brokers that register less than 50 declarations per semester); (ii) declarations assigned to inspectors that relocate to or move away from Toamasina during a given semester but are active for less than two consecutive months in that semester.[16] Our final sample accounts for an average of 76.9 percent of declarations, 78.9 percent of collected taxes, and 76.5 percent of total import value for import declarations subject to taxation and to a physical or a documentary control cleared in Toamasina across the period ranging from January 1 2015 to November 17 2018.[17]

To analyze which declarations are most likely to be subject to corruption agreements we will use measures of excess interaction between inspectors and brokers as proxies for IT manipulation described in Sections

[15]Imports subject to specific clearance procedures (oil and vehicles) are excluded.

[16]Our sample also excludes observations in the top and bottom 2.5% of the yearly distribution of initial average internal reference price, defined as the weighted average of internal reference prices for all items included in the import declaration with weights being the initially submitted weights. The internal reference price for each item is the median unit price (ratio of value to weight) reported across Malagasy importers for a given HS 8-digit-origin country-year.

[17]Our sample ends one year after the start of the delegated randomization of inspector assignment to the third party and a few days before the unveiling of the IT manipulation taking place during this delegated randomization.

4 and 9. The definition of all variables is provided in Appendix Table A1. Here we briefly describe the declaration-level customs outcomes on which we will estimate the impacts of corruption. These are clearance time (measured as the log number of hours from the time the declaration was (last) assigned to an inspector to her assessment of the declaration), a dummy for whether or not fraud was recorded, the change in log value (finally registered - initially declared), tax adjustment, and hypothetical tax revenue losses described below. As additional declaration-level customs outcomes used in robustness exercises we consider the change in log weight (finally registered - initially declared) and the gap between the port authority weight and the initially declared weight (for simplicity called weight gap).

Hypothetical tax revenue losses for a declaration are computed based on the difference between hypothetical tax yield and actual tax yield. Measuring hypothetical tax yield is notoriously challenging given that it is unobserved. Our baseline measure of a declaration's hypothetical tax yield considers as a reference price for each of its items the median unit price (ratio of value to weight) reported across Malagasy importers for the same origin country and year. For each item included in the declaration the relevant reference price is multiplied by the item's weight and the item's tax rate. Summing the resulting hypothetical item-level tax yield across all items included in the declaration yields the declaration-level hypothetical tax yield. This is a conservative measure, for it assumes that the median unit price is not itself under-reported. Our alternative measure of a declaration's hypothetical tax yield considers as a reference price for each of its HS 6-digit products the unit price reported by the exporting country in that year in UN COMTRADE multiplied by the products' weights and by the products' actual tax rates and sums these across all products in the declaration.[18] This measure has the advantage of using prices that are more likely to be exogenous to tax evasion in Madagascar.[19] Two additional measures of hypothetical tax revenue losses are constructed for two subsets of declarations. For declarations for which port authority weight data is available, hypothetical tax yield is constructed also correcting for underreporting of quantities assuming that the measured port authority weight is correct.[20] For declarations for which GasyNet's valuation advice was issued, hypothetical tax yield is constructed as the declaration's advised value multiplied by the average tax rate. As determinants of corruption (and subsequently as controls for evasion risk) we rely on the following *ex-ante* risk characteristics of the import declaration: the tax rate (tariffs and other taxes), the risk score, a dummy for the red channel, a dummy for being a mixed shipment (i.e., one that includes different items), the share of differentiated products as per Rauch (1999)'s classification, and a dummy for

[18] A HS 6-digit product's weight is obtained by summing across the weights of all corresponding items. A HS 6-digit product's tax rate is obtained as the ratio between the sum of actual taxes and the sum of finally declared import value across all corresponding items.

[19] Firms behind a given export flow might conspire with importers in Madagascar issuing fake invoices for them to minimize their tax liabilities. In addition, export unit prices may be downward biased since they are typically recorded as Free On Board (FOB) whereas import prices are recorded Cost Insurance Freight (CIF) and hence include transportation and insurance costs.

[20] We cannot correct quantities declared at the item level since port authority weight is available only for the declaration as a whole. By implication we are assuming that the weight of all items in a declaration is underreported to the same extent.

receiving GasyNet's valuation advice.[21] In robustness exercises we consider other declaration characteristics: the log of the initially declared value, the log of the initially declared weight, the initial unit price relative to median import unit price and the initial hypothetical tax revenue loss (using as reference price the median import price). Summary statistics on all customs outcomes and declaration characteristics are shown in Appendix Tables A3 and A4.

4 Identifying Deviant Declarations

Our identification of declarations suspect of corruption relies on detecting deviations from official rules in the assignment of incoming declarations to customs inspectors. Recall from Section 2 that, according to official rules, incoming declarations should be randomly assigned to inspectors conditional on their productivity. For each inspector, the likelihood of being assigned any given declaration is proportional to her productivity. These rules imply that the process of assigning declarations to inspectors follows a multinomial distribution. Each declaration is assigned to one of K_t possible inspectors, where K_t is the total number of inspectors active in semester t, with corresponding probabilities p_{1t}, p_{2t},. . ., p_{Kt}.[22] These probabilities sum up to 1 because the K_t outcomes are mutually exclusive and can be thought of as reflecting inspectors' relative productivity in semester t. An inspector that is more productive will, on average, handle more declarations than a less productive inspector. Because the marginal distribution of a multinomial distribution is binomial, for each inspector i, the probability of receiving x_{ibt} import declarations from the total number of declarations n_{bt} (where $n_{bt} = \sum_{i=1}^{K_t} x_{ibt}$) registered by broker b in semester t is given by the binomial probability mass function: $P(x_{ibt}|p_{it}, n_{bt}) = \binom{n_{bt}}{x_{ibt}} p_{it}^{x}(1 - p_{it})^{n_{bt}-x_{ibt}}$.

Based on these rules, the share of all declarations that a given inspector handles in a given semester, which we refer to as her inspection share (analogous to the concept of market share in industrial organization), is expected to vary across inspectors, as it depends on their productivity. However, for a given inspector, it should not vary systematically across brokers, unless inspector assignment performed by the IT system did not follow official rules — i.e., was manipulated. All inspectors should have, for a given broker, an inspection share close to their average inspection share.

To assess whether this is indeed the case we consider the import declarations registered by a specific

[21] These variables are supposed to be predetermined from the point of view of the inspectors handling the declaration since they are not the ones lodging the declaration on behalf of the importer, nor are they in charge of issuing a risk score or making the first inspection channel recommendation.

[22] The probability of observing a particular distribution $(x_{1bt}, x_{2bt}, ..., x_{kbt})$ of declarations of a given broker b across inspectors $1, 2, ..., k$ in semester t (where $\sum_{i=1}^{K_t} x_{ibt} = n_{bt}$, the total number of declarations in semester t registered by broker b) given their productivities $(p_{1t}, p_{2t}, ..., p_{kt})$ is:

$$(x_{1bt}, x_{2bt}, ..., x_{kbt}|p_{1t}, p_{2t}, ..., p_k) = \frac{n_{bt}!}{\prod_{i=1}^{K_t} x_{ibt}!} \prod_{i=1}^{K_t} p_{it}^{x_{ibt}}$$

broker during a semester - corresponding to an inspection "market" - and we define for that broker the inspection share of an inspector as the proportion of its declarations handled by that inspector:

$$S_{ibt} = \frac{x_{ibt}}{\sum_{i=1}^{K_t} x_{ibt}} \tag{1}$$

Our measure of potential manipulation of inspector assignment is the deviation between actual assignment and random assignment of declarations to inspectors. Specifically, we define the *excess interaction share* ES_{ibt} as the difference between the actual share of broker b's declarations handled by inspector i in semester t (S_{ibt}) and the predicted share ($\overline{S_{ibt}}$) she would be expected to handle if declaration assignment to inspectors followed official rules:

$$ES_{ibt} = S_{ibt} - \overline{S_{ibt}} \tag{2}$$

To calculate measures of excess interaction between inspectors and brokers we adopt two procedures described in what follows.[23]

4.1 Calibrating excess interaction

A simple procedure to calculate measures of excess interaction is to calibrate predicted inspection shares using the share of all declarations cleared in semester t that were handled by inspector i, and evaluating whether observed inspection shares deviate from these predicted shares. Formally, we set

$$\overline{S_{ibt}} = \overline{p_{it}} = \frac{\sum_{b=1}^{B_t} x_{ibt}}{\sum_{j=1}^{K_t} \sum_{b=1}^{B_t} x_{jbt}} \tag{3}$$

where $\overline{p_{it}}$ is the predicted probability that a declaration registered in semester t will be handled by inspector i and B_t is the number of brokers having registered at least one declaration in semester t. Figure 2 illustrates this procedure: it shows overlaid histograms of the observed distribution of the share of declarations of a given broker cleared by a specific inspector in a given semester (the lighter bars) and the calibrated predicted inspection shares just described (the darker bars). A Kolmogorov-Smirnov test rejects the equality of these two distributions at the 1 percent significance level. Clearly, the observed density distribution of

[23] An alternative strategy to identify deviations from official rules would have been to rely on the workload of each inspector at any point in time and to evaluate whether an incoming declaration was indeed assigned to the active inspector with the lowest workload when that declaration was registered. This would in principle enable us to identify which specific declarations were non-randomly assigned. Unfortunately, the IT system in Madagascar customs does not keep a log of which inspectors were connected at what time nor of the exact time of assignment of a declaration to an inspector, which makes implementing this strategy infeasible.

inspector shares by broker is characterized by higher dispersion and more mass in the upper tail than the predicted distribution. This implies that, relative to the distribution of expected inspection shares, the observed assignment of declarations is characterized by excess interaction between some inspectors and some brokers.

In order to assess whether for a given broker, the observed inspection share of a given inspector is significantly different from the expected inspection share based on random assignment we must take into consideration that these expected inspection shares are not population parameters but estimates thereof. We therefore obtain standard errors for those shares using simulation methods that take five steps.[24] First, we obtain 99 percent confidence intervals for inspectors' productivities using Sison and Glaz's (1995) method of constructing confidence intervals for multinomial proportions. Second, we simulate the productivity distribution across inspectors 1,000 times by drawing from the 99 percent confidence interval of observed productivities (obtained in step 1), conservatively assuming these productivities are uniformly distributed. Third, for each productivity simulation (obtained in step 2), we take the total number of declarations of each broker as given and simulate which inspectors are assigned to her declarations 10,000 times assuming multinomial assignment. Fourth, we test whether the observed number of declarations of a given broker handled by a given inspector is larger than the 99$^{\text{th}}$ percentile of the respective simulated multinomial assignment. Finally, we classify an inspector-broker pair in a given semester as being in significant excess interaction if for at least 99 percent of the productivity simulations we reject the null hypothesis of random assignment.[25]

Table 1 documents the prevalence of non-random assignment in Toamasina over the period ranging from January 1 2015, to November 18 2017, the day before the start of the delegated randomization to the third party. Panel A shows that for 10.3 percent of declarations the (final) inspector handling them interacts significantly more frequently with a broker than would be predicted based on conditional random assignment according to the above described definition. Prima facie, this is evidence of deviations from official rules in the assignment of import declarations of a given broker across inspectors. This non-random assignment is pervasive, with 10 out of 16 inspectors in a typical semester handling at least one non-randomly assigned declaration. This non-random assignment is also persistent over time. For a given pairing of a broker with a particular inspector the excess share of declarations she handles in a given semester is correlated with her excess share in the previous semester, as is shown in Appendix Table A5, suggesting the excess interactions are not accidental.[26]

[24]Since we estimate excess interaction between inspectors and brokers by semester, the five steps to construct standard errors are repeated as many times as there as semesters in the sample.

[25]We consider as a robustness check definitions of significant excess interaction based on at least 95 percent or at least 99.9 percent of the productivity simulations rejecting random assignment.

[26]An inspector-broker pair that is deviant (e.g., characterized by excess interaction relative to non-random assignment) has a 50.6% probability of also being deviant in one (or both) of the subsequent semesters. This conditional probability is approximately 15 times larger than the unconditional probability of a pair being deviant (3.3% as reported in Table 1).

4.2 Estimating excess interaction using logit models

The procedure outlined in the previous subsection has the advantage of being transparent and easy to implement, but it does not account for potential innocent explanations for excess interaction such as fluctuations in inspectors' work schedules and/or differences in inspectors' productivity across days of the week. Descriptive evidence in Appendix Figure A1 and Appendix Table A6 suggests that inspectors and brokers' work schedules are fairly stable and that fluctuations in inspectors' productivity over the workweek are limited. Nonetheless, we address this potential limitation by estimating inspector-semester specific binomial logit assignment models with several control variables, including broker fixed effects, which should have no explanatory power if inspector assignment conformed to official rules.[27]

These models estimate the probability P_{dbit}^{logit} that a declaration d registered by broker b during semester t will be assigned to inspector i instead of all other inspectors active in that semester:

$$P_{dibt}^{logit} = \frac{\exp\left(\beta'_{Xit} X_d + \pi_{pt} + \mu_{it} + \nu_{ibt}\right)}{1 + \exp\left(\beta'_{Xit} X_d + \pi_{pt} + \mu_{it} + \nu_{ibt}\right)}. \quad (4)$$

where the vector of declaration characteristics X_d contains fixed effects for the day of the week the declaration was registered, the tax rate, the risk score, whether the declaration was initially assigned to the physical inspection (red) channel, whether the shipment was mixed, and whether valuation advice was issued, π_{pt} contains product type fixed effects, μ_{it} contains inspector fixed effects, and ν_{ibt} contains broker fixed effects.[28] In this setup, μ_{it} represents a measure of the productivity of inspector i during semester t (a higher value for this parameter means that, all else equal, i will be assigned more declarations). Under the null hypothesis of random assignment, only day of week fixed effects might potentially have explanatory power. The coefficients on all other explanatory variables should be zero. Most notably, broker fixed effects should be insignificant, since the fact that declaration d was registered by broker b should not significantly change the assignment probabilities to a particular inspector.[29]

We estimate binomial logit models using Bayesian Markov Chain Monte Carlo (MCMC) methods to predict the inspection share S_{ibt}^{logit} of inspector i for broker j in semester t, as well as the inspection share

[27]In principle, a multinomial logit model of inspector assignment would be theoretically superior to the inspector-specific logit models we estimate because it would model assignment to all inspectors at once, accounting for the fact that the assignment outcomes of different inspectors are fundamentally interdependent. We tried to estimate such a model but failed to achieve convergence, presumably because including inspector-broker fixed effects in multinomial logit models leads to parameter proliferation.

[28]Product type consist of sixteen groups of HS 2-digit codes following a classification of the World Trade Organization.

[29]A very minor practical drawback of estimating separate logit models for each inspector is that the sum of the predicted probabilities from Equation (4) across inspectors - designated here as P_{dibt}^{logit} - is usually very close to, but not strictly equal to, 1. To address this issue, we normalize the predicted probabilities by reweighting their sum to be equal to 1:

$$P_{dibt}^{logit\ normalized} = \frac{P_{dibt}^{logit}}{\sum_{j=1}^{K_t} P_{djbt}^{logit}}$$

In practice, this does not considerably change assignment probabilities.

inspector i should have for broker j if random assignment was abided by $\overline{S_{ibt}^{logit}}$, and construct estimates of excess interaction ES_{ibt}^{logit}, as the difference between the two.[30] To estimate S_{ibt}^{logit} we use a binomial logit model with all controls shown in Equation (4). To estimate $\overline{S_{ibt}^{logit}}$ we use a binomial logit model that mimics random assignment given by Equation (4) including only day of the week fixed effects in the vector of declaration characteristics. Confidence intervals for S_{ibt}^{logit} and $\overline{S_{ibt}^{logit}}$ are constructed using the Krinsky and Robb [1986] simulation method.[31] Estimates of ES_{ibt}^{logit} (the difference between S_{ibt}^{logit} and $\overline{S_{ibt}^{logit}}$) are therefore driven by broker fixed effects and declaration characteristics other than the day of the week when it was registered.

This procedure has three advantages relative to our first procedure. To start with, it accommodates alternative explanations - such as differences in work schedule and specialization in specific products - for frequent pairings of the same broker with the same inspector. Second and related, it allows us to obtain consistent estimators for broker fixed effects and to test whether they are significant and have explanatory power. Third, by using Bayesian estimation methods and applying shrinkage, we account for the fact that, in a small sample, one might expect some inspector-broker pairs to exhibit apparent excessive interaction even under the null hypothesis.[32] Note that we estimate one logit model per inspector per semester, resulting in a total of 116 different models. Panel B of Table 1 shows the prevalence of non-random assignment in Toamasina based on the measures of excess interaction from inspector-specific binomial logits. For 10.1 percent of declarations the (final) inspector handling them interacts significantly more frequently with a broker than would be predicted based on conditional random assignment. For these declarations the fixed effect of the broker registering them is individually significant in the inspector-specific binomial logit model. We also use a likelihood ratio test to assess whether broker fixed effects are jointly significant in each inspector-semester specific binomial logit model.[33] The results of these tests are reported at the bottom of Panel B in Table 1. On average across semesters, broker fixed effects are jointly significant for close to half the inspectors.

[30]One difference relative to the calibration procedure is that here we use estimates of S_{ibt}^{logit} instead of observed S_{ibt} which facilitates hypothesis testing. Namely, it allows to test the significance of broker fixed effects using likelihood ratio tests.

[31]This simulation method draws a set of parameters from a Normal distribution centered around the point estimates with a covariance matrix equal to the estimated covariance matrix. These parameters are used to calculate assignment probabilities to each inspector for each declaration. Taking the average of these probabilities across all declarations registered by broker b yields the share that is expected to be assigned to inspector i: S_{ibt}^{logit} in the model with all controls and $\overline{S_{ibt}^{logit}}$ in the model that mimics random assignment. The difference between S_{ibt}^{logit} and $\overline{S_{ibt}^{logit}}$ gives ES_{ibt}^{logit} for each iteration. This simulation method is repeated 1,000 times. For such large number of iterations, the simulated distribution of assignment probabilities approximates the real distribution of assignment probabilities. This simulation method provides (i) the point estimate for ES_{ibt}^{logit} obtained as the average of ES_{ibt}^{logit} across the 1,000 iterations and (ii) an indicator for whether ES_{ibt}^{logit} is significantly larger than 0 (i.e., whether S_{ibt}^{logit} is significantly larger than $\overline{S_{ibt}^{logit}}$).

[32]In principle, random inspector-specific logit models would be preferable to the standard logit models we estimate as they would allow random broker effects and productivity parameters. We tried to estimate such models but failed to obtain convergence, as in the case of the multinomial logit models, possibly due to parameter proliferation.

[33]In order to conduct these tests, we estimate a third type of logit model with all controls but excluding *only* broker fixed effects. This ensures that the significance of these fixed effects can be assessed by comparing estimates from this third type of logit model to those from the model with all controls (including broker fixed effects).

Ultimately, the two different procedures yield very similar measures of excess interaction. The correlation between excess interaction measures based on inspector-specific logit models (ES^{logit}) and those calibrated from observed inspection shares (ES) is 0.97 (as is shown in Appendix Figure A2). Given this high correlation between measures derived from the two procedures we will predominantly focus on the measures of excess interaction based on calibration. However, we replicate our main results using estimates from the binomial logit models and show that our main findings are robust to the use of that procedure (see Appendix Tables A9 and A10).

We end this section by emphasizing that detecting deviations from random assignment is neither necessary nor sufficient to establish potential corruption, and highlighting some properties of our excess interaction measures that are relevant for their appropriate interpretation. First, our measures vary across pairs of inspectors and brokers within a semester but all declarations of a given broker handled by a particular inspector in a given semester are characterized by the same excess interaction share. Inevitably some of those declarations may not have been manipulated but will be characterized by excess interaction, which implies that we may be overestimating the prevalence of manipulation of inspector assignment but underestimating differences between manipulated and non-manipulated declarations.

Second, our excess interaction measures have potential for false positives. This concern is partially mitigated by our use of simulation methods to identify excess interaction that is statistically significant and the use of binomial logit estimation procedures. Nonetheless, detecting potential deviations is merely the first step in the process of uncovering potential corruption. The findings in Sections 5 and 6 showing that the declarations of brokers interacting excessively with some inspectors are at a significantly higher risk of tax evasion and that inspectors treat preferentially the declarations of brokers with whom they interact excessively frequently reduce the concern of false positives and suggest deviations are not accidental.

Third, our excess interaction measures also have potential for false negatives since they identify only one particular form of corruption. Our measures do not capture the (rather plausible) possibility that corrupt dealings are made between randomly assigned inspectors, brokers and/or importers. In an extreme scenario a cartel led by the manager (that heads the inspectors) could set the terms of the bribes and make the identity of the inspector assigned to each declaration irrelevant. Our excess interaction measures would not reject the null of excess interaction while in fact corruption would be ubiquitous. This extreme scenario is not supported by our evidence in Table 1 which suggests not all inspectors participated. But this caveat points to a requirement for our measures of excess interaction to be able to identify corruption: the need for differences across inspectors in their propensity to enter into corrupt deals with brokers. By agreeing deals ex ante brokers can be sure that their declaration ends up with the "right" inspector. Moreover, it minimizes the risk of detection as inspectors clear undervalued shipments very quickly (with negotiations about bribes and the division of surplus taking place before the goods arrive). The presence of false negatives implies that our approach may provide an underestimate of the prevalence and consequences of corruption in Madagascar customs.

Finally, we conduct a placebo test by constructing calibrated excess interaction measures for two sets of import declarations excluded from our main sample: imports that entered under non-taxable customs regimes and imports made by importers part of a trade facilitation program for accelerated clearance that are not inspected (although an inspector is assigned). For both these types of declarations, incentives to manipulate inspector assignment are limited because they are either exempt from taxes or from inspector assessment. The share of declarations subject to excess interaction for those two types of declarations is extremely low: 0 percent for non-taxable customs regimes and 1 percent for the trade facilitation program.[34]

4.3 Who manipulates?

Who is responsible for this non-random assignment: the IT team that manipulates the IT system's initial assignment or the customs port manager who manually and voluntarily erases the initial assignment and reassigns declarations? To answer this question, Figure 3.a plots the density distributions of the initial inspector assignment made by the IT system (the long-dashed line) as well as the final assignment (the short-dashed line) which reflects both the initial assignment and potential re-assignments of declarations to inspectors made by the customs port manager. The distributions of initial and final inspector assignment are very similar, and both deviate markedly from that of predicted assignment if official rules were adhered to (the solid line). This is perhaps not surprising since re-assignments are rare, only happening in 6 percent of cases. Thus, manipulation of the IT system appears to be the predominant driver of non-random assignment.

The port manager nonetheless appears to be complicit in the corruption scheme. Focusing *only* on declarations re-assigned by the port manager, Figure 3.b reveals that these re-assignments exacerbate, rather than reduce, non-random assignment. Instead of offsetting excess interaction, the port manager appears to be reinforcing it. If he were to choose inspectors randomly when reassigning declarations, one might have expected the final distribution to be less skewed.[35]

The fact that certain brokers' declarations are not randomly assigned to inspectors was confirmed in inspector interviews in Toamasina. One inspector mentioned *"I have been here 7 months, but there are certain brokers whose declarations I have never handled"*. Another complained *"I never get the good declarations"*. Our interpretation that such non-random assignment results from IT manipulation is consistent with the remarks by an external auditor of Madagascar's customs IT system of an *"over-reliance on IT administrator*

[34] The number of declarations under non-taxable customs regimes is 4,693 and that under the trade facilitation program is 12,181.

[35] If the port manager instructed the IT department before the initial inspector assignment is made, he would be playing a more meaningful role in the corruption scheme. Unfortunately, it is not possible to test this possibility with our data. More generally, we are not able to ascertain who initiates the scheme.

account, which is typically used at most a few times a year to make major systemic changes, but was used multiple times a day in Madagascar. The IT administrator account allows you to override basic settings." and of *"...surprising and suspiciously long queues outside the office of the head of the IT department, which normally is not a client-facing function"*. When we confronted the port manager with our initial analysis he acknowledged that manipulation of inspector assignment was prevalent.

Based on the findings of an early incarnation of this paper a number of customs inspectors were sanctioned for corruption and removed from their posts. The assignment of declarations was delegated to the third party GasyNet, which agreed to randomize the assignment of declarations to inspectors. This delegated randomization provides an opportunity to assess whether we are indeed identifying IT manipulation that we will exploit in Section 9.

5 Do Deviant Declarations Exhibit a Higher Risk of Tax Evasion?

If excess interactions were the product of accidental deviations from official rules in inspector assignment, then the characteristics of these declarations should not systematically differ from those of other declarations. In contrast, if excess interactions were the product of deliberate IT manipulation to assign a specific declaration to a preferred inspector with whom the broker has a corruption agreement, then a higher risk of customs fraud, which would indicate higher susceptibility to tax evasion, would be expected for such declarations.

On average, declarations characterized by higher excess interaction shares have higher risk scores and are subject to higher tax rates, as is shown in Figures 4.a and 4.b, which present polynomial plots of these risk characteristics against the excess interaction share. By contrast, initial unit prices relative to median import unit prices tend to fall with the excess interaction share, as shown in Figure 4.c, suggesting that declarations of brokers that interact excessively with some inspectors are more likely to be undervalued. The excess interaction share is indeed positively correlated with hypothetical tax revenue losses calculated on the basis of the initial registration of the declaration by the broker (that is, before the inspector assesses the declaration and carries out any adjustment), as shown in Figure 4.d.

Table 2 presents estimates of unconditional bivariate ordinary least squares (OLS) regressions of declaration characteristics commonly associated with tax evasion on the excess interaction share. The standard errors are two-way clustered by inspector and by broker. A 10 percent (0.10) increase in the excess interaction share is associated with an increase in the risk score of half a point, a 3.1 percent higher tax rate, a 7.8 percent increase in the probability the declaration contains multiple HS6 products (i.e. is mixed), a 5 percent increase in the share of the declaration's value accounted for by differentiated products, a 9.4 percent increase in the probability of valuation advice being issued, and a 5.9 percent decrease in the initial price relative to median import price. These significantly lower initial prices may explain why the excess interaction share is not significantly correlated with the initially declared value, despite being associated with a higher initially declared weight. Consistent with this interpretation of undervaluation, a 10 percent increase in the excess interaction share is associated with a 6.3 percent increase in initial (i.e., before any adjustment made by customs) hypothetical tax revenue losses.

Note that because declarations subject to excess interaction are subject to higher taxes and tend to be larger (in weight), they are subject to a substantially higher theoretical tax liability. Figure 4.e shows that declarations subject to excess interaction are significantly more likely to be "high potential tax yield" declarations - defined as those for which the hypothetical tax yield based on external reference prices exceeds 20 thousand USD for which the incentives to evade are largest.[36] While only 1 in 4 declarations not subject to significant excess interaction are high potential yield declarations, half of all declarations subject to significant excess interaction are (see Appendix Table A3).

In short, declarations characterized by excess interaction have characteristics commonly associated with an elevated risk of tax evasion.[37] Appendix Table A7 presents regressions examining the determinants of the excess interaction share. The risk score and issuance of valuation advice (a proxy for undervaluation) are the most salient predictors of deviations from conditional random assignment of inspectors to declarations. The evidence of declarations with higher excess interaction shares being at a higher risk of tax evasion is confirmed using excess interaction measures based on binomial logit models (see Appendix Table A9).

6 Are Deviant Declarations Treated Differently?

This section assesses whether inspectors treat the deviant declarations differently - in a preferential manner - from other declarations. If excess interactions were accidental, then inspectors should provide no differential treatment to deviant declarations, beyond the increased scrutiny that may be legitimately expected as these declarations were shown to be at a higher risk for tax evasion in Section 5. Similarly, if IT department staff was simply bribed to assign certain declarations to the least competent inspector, we would not necessarily expect the chosen inspector to treat manipulated declarations any differently from the way she handles other declarations. Inspectors complicit in a corruption agreement, by contrast, would plausibly provide, in exchange for a bribe, preferential treatment to manipulated declarations. To assess whether inspectors treat deviant declarations - those of brokers with whom they interact excessively - differently than other

[36] The cutoff of 20 thousand USD corresponds roughly to the top quartile of the hypothetical tax revenue yield distribution.

[37] An alternative explanation for these findings is that inspectors offer discounts to certain importers to maximize future tariff revenue. However, Appendix Table A8 shows that excess interaction is not correlated with proxies for the average trade elasticity of products included in the declaration based on Broda and Weinstein (2006) and Fontagne et al. (2022), nor with the average durability or "stickiness" of trade relationships based on Martin et al. (2020) of the products included in the declaration. This suggests inspectors are not targeting importers with the highest sensitivity to tariff discounts.

declarations, the following specification is estimated by OLS:

$$Y_d = \beta_E ES_{ibt} + \beta_X X_d + \mu_i + \nu_b + \kappa_c + \pi_p + \tau_m + \epsilon \tag{5}$$

where Y_d is one of the declaration-level customs outcomes described in Section 3 (clearance time, fraud records, value and tax adjustments, hypothetical tax revenue losses). The main regressor of interest is the excess interaction share ES_{ibt} defined in Section 4. The vector of declaration characteristics X_d includes the tax rate, the risk score, a dummy for the red channel, a dummy for being a mixed shipment, the share of differentiated products, and a dummy for GasyNet's valuation advice. Inspector fixed effects μ_i, broker fixed effects ν_b, HS 2-digit product fixed effects π_p, source country fixed effects κ_c, and month-year fixed effects τ_m are also controlled for. The independent and identically distributed (i.i.d) error is ϵ.

The inclusion of inspector fixed effects accounts for heterogeneity across inspectors in their average productivity, ability, work ethic, and other time-invariant characteristics that may impact their performance. Broker fixed effects account for heterogeneity in their import patterns, efficacy, record-keeping, and other characteristics that may impact customs clearance. Since average differences in inspector and broker characteristics are accounted for, the specification is stringent in that identification of the coefficient on the excess interaction share is based on the interaction between the inspector and broker relative to other pairings of inspectors and brokers. Standard errors are clustered two-way by inspector and by broker.[38]

6.1 Main Findings

The results from estimating Equation (5) are shown in Table 3. Inspectors assess declarations registered by brokers with whom they interact excessively frequently significantly faster than other declarations. Column (1) implies that a 10 percent increase in the excess interaction share is associated with a 20 percent (or approximately a 4-hour) reduction in clearance times. Declarations characterized by excess interaction are also less likely to be deemed fraudulent: column (2) shows that a 10 percent increase in the excess interaction share is associated with a 2.8 percent reduction in the likelihood of fraud being recorded. This is a large effect given that the unconditional probability of fraud being recorded is 8 percent (see Appendix Table A3).

In the same vein, columns (3) and (4) show that value and tax adjustments are significantly lower for declarations characterized by excess interaction. A 10 percent increase in the excess interaction share is linked to a 0.8 percent lower increase in value and a 0.9 percent lower increase in tax yield. These are again sizeable effects given that the unconditional averages of value and tax adjustment are 2 percent.

[38] Due to the inclusion of a large set of fixed effects, our estimates are obtained using the reghdfe Stata command drawing on Guimaraes and Portugal (2010). The current version of the command eliminates from the number of observations singletons and adjusts standard errors for their exclusion. A singleton is an observation unique in the sample in having a given fixed effect equal to one: e.g., a declaration with imports from source country A if no other declaration reports importing from country A.

The significantly lower likelihood of the tax burden being revised upwards is perturbing since declarations characterized by excess interaction are more likely to be undervalued to start with, as shown in Section 5. Inspectors thus seem to exacerbate, rather than reduce, the disparities between declarations characterized by excess interaction and other declarations. As a result, excess interaction is associated with sizeable tax revenue losses. Column (5) implies that a 10 percent increase in the excess interaction share is associated with a tax revenue loss of 3.9 percent.

In summary, inspectors treat the declarations of brokers with whom they interact excessively frequently preferentially: they clear these declarations more quickly and subject them to significantly laxer tax enforcement. If inspectors were honest, no preferential treatment should be observed.

6.2 Robustness Checks

We subject these findings of preferential treatment by inspectors to several robustness checks. First, we estimate Equation (5) using the measures of excess interaction based on inspector-specific logit models. The results, presented in Appendix Table A10, provide clear evidence of preferential treatment given by inspectors to the declarations of brokers with whom they interact excessively frequently. Second, to address potential selection bias, we rely on a propensity score matching approach described in Appendix B to identify a set of control declarations that are most similar to those that are treated, i.e., have significant excess interaction, based on observable risk characteristics.[39] The results from estimating Equation (5) for the matched sample (panel A) or using propensity score weighted least squares as proposed by Hirano et al. (2003) (panel B) are shown in Table A12 and consistent with our main findings displayed in Table 3.[40] Third, we estimate variants of Equation (5) that progressively add the different types of fixed effects (panels A-D) instead of including them all at once, and control for all risk characteristics considered in Table 2 (panel E) and find the patterns of preferential treatment by inspectors to declarations with excess interaction to be maintained in Appendix Table A13.[41] Fourth, we add more stringent types of fixed effects to Equation (5): inspector-semester and broker-semester; inspector-month and broker-month; inspector-semester, broker-semester and importer-semester; or importer-broker. Appendix Table A15 shows that these fixed effects do not impact the qualitative pattern of results. Fifth, we estimate Equation (5) using either the indicator for significant excess interaction defined in Section 4 (instead of the excess interaction share) or two other indicators based on significance levels of 95 percent or 99.9 percent. The findings in panels A-C of Appendix Table A16 are qualitatively similar to those in Table 3. Finally, we construct measures of excess interaction for three alternative samples that modify the restrictions described

[39]The balance tests for this propensity matching approach shown in Appendix Table A11 indicate no significant differences on average across treated and control declarations on all but two of those risk characteristics: the probability of receiving valuation advice and the tax rate (the latter at a 10% significance level only).

[40]The number of observations in panel A of Table A12 is substantially smaller than in Table 3 since our matching approach uses the nearest neighbor matching algorithm that selects for each treated declaration a single control declaration.

[41]We also shown that the results are robust to different types of clustering of standard errors in Appendix Table A14.

in Section 3: a sample excluding only brokers registering less than 20 declarations per semester (versus 50 in our main sample), a sample excluding brokers registering less than 100 declarations per semester, and a sample not excluding any brokers. The estimates of Equation (5) for these three samples shown in panels D-F of Appendix Table A16 are qualitatively unchanged relative to those in Table 3.

6.3 Alternative Explanations

This section evaluates salient alternative explanations for the findings of differential preferential treatment of deviant declarations by inspectors by running a set of additional tests. To start with, one possibility is that our excess interaction share merely reflects "familiarity" between inspector and broker, whereby the fact that certain brokers interact very frequently with an inspector reduces fixed inspection costs. Alternatively, inspectors may update their prior beliefs about brokers' likely compliance based on their past interactions with them and consequently be less likely to scrutinize brokers with whom they interact frequently for which they have a sizable pool of past interactions to base their inferences on. To assess the validity of these explanations for our results, we add to Equation (5) a measure of "familiarity": the total number of prior transactions of that same broker cleared by the same inspector over the preceding semester.[42] The results in Table 4 (panel A) show that the familiarity measure itself has some predictive power: it is linked to slightly higher tax revenue losses, but does not significantly predict the incidence of fraud or value adjustment. More importantly for our purposes, controlling for familiarity only marginally reduces the impact of the excess interaction share which remains strongly statistically significant in all specifications. Put differently, the results do not appear to be driven by familiarity or learning, which, in any case, cannot explain why deviant declarations would be more risky to start with.

A second possible explanation for differential treatment is that it reflects congestion and fluctuations in inspectors' workload. Specifically, when inspectors get very busy they may be tempted to exert less scrutiny and speed up clearance merely to be able to manage increased traffic. If this increase in their workload is generated by absenteeism of other inspectors, we might see a simultaneous increase in the excess interaction share and a decrease in scrutiny and clearance times. To control for such congestion, we add to Equation (5) the number of declarations assigned to a given inspector over the course of the calendar month as a proxy for their workload. While Table 4 (panel B) shows that this measure of congestion is clearly positively correlated with clearance time, the impact of the excess interaction share on the other customs outcomes is hardly affected by its inclusion.[43]

Third, one may worry that the patterns documented are an artefact of dubious declarations being more

[42] Our excess interaction share measure is based on identifying deviations in the share of a given broker's declarations handled by a given inspector. By contrast, the familiarity measure is based on the absolute number of interactions between the broker and the inspector. Whereas inspectors will interact more with large brokers, and hence be more "familiar" with them, they will not necessarily interact excessively with large brokers, since our excess interaction share is a relative measure.

[43] Similarly, as mentioned above, Appendix Table A15 shows that the results are robust to controlling for inspector-month and broker-month fixed effects, which can also proxy for workload and congestion.

likely to be registered outside of regular business hours, i.e., late in the evening, at night, or during the weekend. This could help explain excess interaction since there are typically much fewer inspectors active and they may monitor incoming declarations less aggressively because they are fatigued and/or want to go home. However, Table 4 (panel C) shows that the results are robust to excluding declarations registered outside of regular business hours, which account for less than 3 percent of all declarations.

Fourth, one may be concerned that the results are driven by (excess) interaction between inspectors and importers themselves rather than brokers, who are supposed to represent the interests of importers. We address this possibility in two ways. We augment Equation (5) with importer fixed effects in Table 4 (panel D) and this hardly impacts the qualitative pattern of results.[44] In Table 4 (panel E) we add to Equation (5) the excess interaction share between importers and inspectors. The measure is defined analogously to the calibrated excess interaction share between brokers and inspectors, for importers that registered at least 50 declarations during the semester, which leads to a reduction in sample size. The excess interaction share between inspectors and importers neither significantly predicts fraud, nor value nor tax adjustment, and does not seem correlated with tax revenue losses. By contrast, the excess interaction share between inspectors and brokers remains robustly significant. These results justify our focus on brokers rather than importers. The fact that brokers seem to be the primary protagonists of the specific corruption scheme we document may be because they have more to gain from it; there are far fewer brokers than importers, and brokers interact more frequently with inspectors than importers do. Moreover, lobbying customs is the core business of brokers in many developing countries.

Yet, it is worth noting that while most importers work exclusively with one broker, Appendix Table A17 furnishes evidence that importers who use multiple brokers systematically steer their most risky declarations to brokers with the highest propensity to have excess interaction. It is difficult to ascertain, however, whether they do so because they know about the corruption scheme or whether they were simply offered favorable terms by brokers engaging in excess interaction.

Fifth, given the limited number of inspectors working in Toamasina one may worry that our results are driven by a few individuals, rather than reflecting widespread corruption. Table 4 (panel F) replicates our baseline results but excluding for each semester the top three inspectors with the greatest share of declarations with significant excess interaction. The coefficients remain statistically significant and of similar magnitude as our baseline results. The results are thus not driven by a select few inspectors (even though the tax revenue losses associated with the scheme are very concentrated, as we will show in section 8). Evidence that the results are also not driven by a select few brokers is provided in Appendix Table A14 where we exclude for each semester the top five brokers with the greatest share of declarations with significant excess interaction.

[44] Appendix Table A15 shows that including importer-broker fixed effects does not qualitatively change results either.

Sixth, another potential concern is that results might be driven by inspectors specializing in clearing different goods. This concern is mitigated by the fact that, formally, there is no specialization across different inspectors: they all clear the same set of goods. However, one may nonetheless wonder whether the IT department staff who are manipulating assignment are systematically assigning declarations containing certain products to unwitting inspectors that do not have the requisite expertise to adequately evaluate them; they may be seeking out inspectors that are the worst at detecting fraud for particular sets of products. To address this concern, Appendix Table A18 presents regressions where the unit of observation is an item (recall that a declaration can contain multiple items). The dependent variables are the log of the initially declared unit price, adjustments in that unit price, the finally registered unit price, the adjustment in weight (finally registered - initially declared) and an item-specific measure of the hypothetical tax revenue loss. The main regressor of interest is still the excess interaction share and the set of controls now includes HS 8-digit product-inspector fixed effects, broker fixed effects, source country fixed effects, month-year fixed effects, and a vector of both declaration characteristics (the risk score, a dummy for the red channel, a dummy for being a mixed shipment, a dummy for GasyNet's valuation advice) and the item-specific tax rate. The HS 8-digit product-inspector fixed effects capture the comparative advantage of the inspector in detecting fraud in different types of products. The item-level initially declared unit price is significantly negatively correlated with excess interaction (column (1)). Excess interaction is associated with a lower item-level initial unit price but also with significantly lower adjustments to the unit price. As a result, the final unit price is even more negatively correlated with excess interaction. Excess interaction is also associated with lower weight adjustment and higher potential tax revenue losses, but these associations are not statistically significant at conventional significance levels.

Seventh, evidence of heterogeneity in the differential treatment of deviant declarations is hard to reconcile with explanations other than corruption for our main results. We estimate Equation (5) allowing the excess interaction share to be interacted with the tax rate. Differential treatment by inspectors that interact excessively frequently with a given broker appears particularly pronounced for declarations subject to higher taxes: these are especially less likely to be deemed fraudulent and exhibit significantly higher tax revenue losses, as seen in in Appendix Table A19.

Some final evidence consistent with corruption is provided by the analysis of inspector re-assignments made by the customs port manager. Such re-assignments are substantially more likely when declarations are initially assigned to an inspector with whom the broker is not interacting excessively frequently (see Appendix Table A20). This is inconsistent with re-assignments being random. Moreover re-assigned declarations typically yield higher fraud findings, value and tax adjustments. This is especially the case if they are taken away from inspectors with initial excess interaction, suggesting that these non-randomly assigned declarations were more risky to start with. By contrast, re-assigned declarations from inspectors without excess interaction towards inspectors with excess interaction do not yield increased fraud findings or tax adjustments, as is shown in Appendix Table A21.

7 How Costly Is Corruption?

How much tax revenue is lost because of the corruption scheme we document? To answer this question, we calculate how much more tax revenue would have been collected if there was no significant excess interaction between inspectors and brokers.[45] The key input into this back-of-the-envelope calculation are estimates of the impact of excess interaction between inspectors and brokers - β_E in Equation (5) - on tax revenue losses. We focus on a measure of hypothetical tax revenue losses described in Section 3 that accounts for underreporting of quantities and is based on prices reported by countries exporting to Madagascar, which are arguably less likely to be endogenous to underinvoicing in Madagascar.[46] Additionally, to rely on an unbiased estimate of the overall impact of corruption on tax revenue losses, we estimate Equation (5) including only controls that are plausibly exogenous to corruption: the tax rate, the dummy for mixed shipment, the share of differentiated products, source country fixed effects, HS 2-digit product fixed effects and month-year fixed effects.[47] Our β_E estimate (presented in column (11) of Panel B in Appendix Table A22) indicates that a 10 percent increase in the excess interaction share is associated with a 21 percent increase in tax revenue losses.

Using this estimate, we calculate for each declaration the counterfactual tax revenue that would have been collected in the absence of significant excess interaction between inspectors and brokers as $T^{NC} = T * exp(\widehat{\beta_E * ES})$, where T is the actual tax yield.[48] We are effectively asking how much more tax revenue would have been collected if declarations subject to excess interaction had been treated by inspectors like declarations that were not. The results of this exercise are presented in Appendix Table A24 (panel A) for declarations characterized by significant excess interaction (in the first two columns) and for all declarations (in the last two columns). Interestingly, declarations with significant excess interaction yield more tax revenue, 11,423 USD on average, despite being undervalued, than the average declaration with 10,446 USD. This finding is consistent with declarations with significant excess interaction being subject to a higher tax liability, as was shown in Section 5. In the absence of corruption, the average declaration with significant excess interaction would have yielded an additional 2,962 USD in tax revenue. Put differently, the tax yield on declarations likely to be the object of corruption agreements would have been 26 percent higher. This number is a lower bound on total tax revenue losses per declaration associated with corruption

[45] We abstract from dynamic effects of offering tariff discounts today on future tariff revenues and from uncertainty about tariff rates. Importantly, note that we do not evaluate the social welfare effects of the prevailing tariff structure nor those of the corruption scheme we unveil.

[46] Results for all other measures of hypothetical tax revenue losses described in Section 3 are reported in Appendix C .

[47] The controls in Equation (5) potentially endogenous to corruption are inspector and broker fixed effects and the risk score.

[48] The details of this calculation are provided in Appendix C.

since the set of declarations characterized by significant excess interaction likely also includes some that were randomly assigned and not the object of corruption schemes. Across all declarations, average (and hence aggregate) tax yield would have been 3 percent higher in the period before the delegated randomization intervention. These estimates do not reflect the gains associated with eliminating tax evasion altogether, but only the gains from eliminating tax evasion due to the specific corruption scheme we uncover. Our methodology does not address the (rather plausible) possibility that tax evasion can also result from deals made between randomly assigned inspectors, brokers and/or importers.[49]

8 Who Benefits from Corruption?

This section analyses which types of inspectors and brokers participated in the corruption scheme and tries to shed light on how much they gained by doing so.

8.1 Which Inspectors and Brokers Participated?

We start by assessing which types of inspectors participated in the scheme by regressing the average share of declarations handled by the inspector subject to significant excess interaction on a number of inspector characteristics. The results are presented in panel A of Appendix Table A25. Tenure is by far the strongest predictor of handling declarations characterized by excess interaction, but the effect is highly non-linear: new inspectors (the omitted category) have a significantly lower propensity to handle declarations subject to excess interaction than more established inspectors and this association is robust to controlling for inspector age (column (2)). There is some evidence that male inspectors handle a larger share of declarations subject to excess interaction, but the difference with their female colleagues is only borderline statistically significant at the 10 percent level and loses significance when controlling for age. For the subset of inspectors for which we have information on educational attainment, we find those with a management degree have a higher propensity to handle declarations subject to excess interaction (column (3)).

Comparable estimates for brokers are presented in panel B of Appendix Table A25. Brokers based in Toamasina handle a significantly higher share of declarations assessed by inspectors with whom they interact excessively. On average, the share of declarations they handle that is subject to excess interaction is 5.9 percent higher than the average share of non-Toamasina based brokers and the difference is significant at the 10 percent level. However, this association loses significance once we include a dummy identifying brokers that import on behalf of only one importer (column (2)) and when we control for the broker's average share of all declarations and for broker tenure (column (3)). Though none of the results are significant

[49]These calculations do not take into account potential beneficial impacts of tariff discounts on future trade volumes: lower levels of taxes may encourage imports in subsequent periods. More generally, customs administrations have the dual objective of facilitating trade and collecting tax revenues and these objectives may conflict with one another both in the short- and in the long-run because of such dynamic effects.

at conventional significance levels, they suggest that brokers who serve only one importer exhibit lower excess interaction. Brokers who have been active for a longer period of time tend to have more declarations subject to excess interaction.

Finally, for 20 inspectors that participated in the survey of inspectors we implemented in 2017 we are able to correlate their views with the share of declarations they handled that were subject to excess interaction. Appendix Table A26 shows that inspectors with a higher share of declarations with excess interaction report on average significantly higher overall job (but not pay) satisfaction, higher esprit de corps, and are much more likely to claim that they know the most fraudulent firms.[50]

Taken together, the fact that excess interaction increases with inspector tenure and that brokers based in Toamasina have a higher propensity to handle declarations with excess interaction points to the importance of establishing personal relationships and private information acquisition.

8.2 How Are Tax Revenue Losses Distributed?

Unfortunately, our data do not allow us to identify how participants in the corruption scheme divided the surplus generated by tax savings associated with the scheme; it is thus not possible to precisely pinpoint how much each participant gained, which is furthermore complicated by the fact that officials in the IT department, the port manager, and importers likely also have taken a cut. Instead, we present estimates of the distribution of tax revenue losses across inspectors and brokers by semester, ranking inspectors and brokers in terms of their contribution to overall revenue losses (with rank 1 assigned to the inspector or broker with the highest revenue losses in a given semester), using our preferred measure of counterfactual additional tax yield (calculated using external reference prices and correcting for potential underreporting of quantities) if there had not been significant excess interaction.

Table 5 reports that on average an inspector collects 4.8 million USD worth of tax revenue per semester (6 percent of total taxes collected in the port per semester). Average tax revenue losses associated with the unveiled corruption scheme equal 140 thousand USD per inspector per semester (3 percent of the revenues they collect). Yet, this number masks large heterogeneity across inspectors. In a typical semester, the inspector accountable for the largest tax revenue losses incurs 677 thousand USD worth of losses - roughly 4 times the average loss. Yet, she also collects 6.5 million USD worth of taxes (or 8 percent of total taxes collected in the port per semester). Hence, over the period considered, tax revenues collected by the "top" inspector would have been 11 percent higher without the corruption scheme.

Despite fairly widespread participation of inspectors in the scheme (documented in Table 1), the tax losses associated with participation in the corruption scheme are highly concentrated: the “top” inspector

[50] Excess interaction is not significantly correlated with pay satisfaction, views about the adequacy of training, discretion, perceived corruption (among brokers, colleagues, and supervisors), punishment for unethical behavior, reporting of threats by brokers, nor meritocracy.

accounts for roughly one third of the total revenue losses associated with the scheme in a given semester, the "top" two inspectors jointly account for more than half (55 percent) of all revenue losses, and the top 3 inspectors jointly account for more than two thirds of all revenue losses. These statistics attest to the granularity of tax evasion associated with the scheme; if each semester the top three most corrupt inspectors had not participated in the scheme, overall tax revenue collection in the port would have been almost 2 percent higher (as opposed to 3 percent if none of the inspectors had participated). The behavior of a select few inspectors thus has macro-fiscal implications.

The concentration of tax revenue losses in the hands of a select few inspectors begs the question as to why corruption was neither detected nor sanctioned sooner. The answer to this question may partly lie in the targeting of declarations subject to high tax liability noted in Section 5. Figure 5.a plots the tax yield per declaration against the excess interaction share. If anything, the relationship between tax yield and excess interaction is positive. Inspectors with more excess interaction have *higher* average (unconditional) tax yields per declaration, as is shown in Appendix Figure A3. This helps explain why conventional inspector performance metrics - such as total tax yield or average tax yield per declaration - may not obviously point to corruption. In fact, based on tax revenue collection numbers alone one might be tempted to conclude that many of the inspectors with the highest excess interaction are top performers.

Figure 5.b reveals, however, that such conclusion would be driven by selection that masks important performance differences. Dividing declarations into "high potential yield" declarations (with a hypothetical tax yield based on external reference prices exceeding 20 thousand USD) and "low potential yield" (all other declarations) reveals that the association between the excess interaction share and tax yield is clearly negative for "high potential yield" declarations and inexistent for other declarations. Inspectors with more excess interaction collect substantially less tax revenue on these "high potential yield" declarations. Yet, their average tax yield across all declarations is higher despite their inferior performance simply because they attract a higher share of such "high potential yield" declarations, as was shown in Figure 4.e (recall that declarations subject to excess interaction are significantly more likely to be "high potential yield" declarations).[51] The ability of corrupt inspectors to appropriate lucrative declarations thus helps explain why they manage to collect more taxes on average despite turning a blind eye on undervaluation among some of the most valuable declarations. Perversely, the inspectors who are most implicated in the corruption scheme and responsible for the largest revenue losses, presumably pocketing the biggest illegal bribes, also exhibit nominally superior revenue collection performance.

Tax revenue losses associated with the corruption scheme are also very concentrated among a fairly limited set of brokers, as is shown in panel B of Table 5. The broker accountable for the largest revenue

[51] Appendix Figure A4 plots the average inspection share of each inspector per semester against the share of declarations subject to excess interaction and shows that inspectors with more excess interaction assess a higher share of "high potential yield" declarations.

losses in a given semester on average pays 1.7 million USD worth of taxes (or roughly 2.3 percent of the total taxes collected in our sample in a given semester) but at the same time evades 514 thousand USD worth of taxes. In other words, their total tax liability would be 29 percent higher without the corruption scheme. The "top" 3 brokers in terms of their contribution to overall tax revenue losses account for half of all revenue losses, the "top" 5 brokers account for 71.5 percent of revenue losses associated with the scheme but only for 17 percent of overall tax revenue.

9 Did Delegated Randomization of Inspector Assignment Curb Corruption?

After presenting a preliminary version of this paper to the Director General (DG) of customs, internal audits were launched and a number of inspectors were either sanctioned for corruption or strongly encouraged to opt for voluntary retirement and the head of the IT department was suspended. The DG also decided to reform the assignment of declarations to inspectors, by delegating it to the third-party GasyNet. Using its own software, GasyNet randomly assigned declarations to active inspectors. This delegated randomization intervention provides us with a unique opportunity to assess whether the excess interactions we document are indeed the product of IT manipulation and hence to validate our methodology to detect corruption. It simultaneously offers a case study of the effectiveness of IT interventions to curb corruption and reduce fraud.[52]

9.1 Prevalence of Excess Interaction During Delegated Randomization Period

The delegated randomization of inspector assignment started on November 18, 2017 and led to the virtual disappearance of excess interaction, as is shown in Figure 6 which plots the evolution of the share of declarations characterized by significant excess interaction after automatic assignment. While the prevalence of excess interaction trended upward in the period preceding the delegated randomization intervention, it suddenly and precipitously fell to nearly zero after the start of delegated randomization indicated by the vertical bar in the graph. The delegated randomization intervention thus effectively eliminated excess interaction between inspectors and brokers.

However, approximately four months after the start of the delegated randomization intervention excess interaction resurfaced, plausibly driven by a new form of IT manipulation: the withholding of certain declarations from the delegated randomization. IT department staff complicit in the corruption scheme figured out a way to temporarily shut down the automatic notification that GasyNet receives when a

[52] However note that the reform exploited in our analysis is not a natural experiment and thus causal claims from its impact need to be taken with caution.

declaration is registered, thus preventing GasyNet from randomizing the inspector assignment of these declarations. Approximately 7 percent of declarations (1,275 declarations out of 17,736 declarations registered in the delegated randomization period) were withheld from delegated randomization. These declarations were readily identified by comparing the set of declarations randomized by GasyNet to the set of declarations that cleared customs daily. The set of declarations withheld from delegated randomization likely includes declarations that were not deliberately "targeted" to bypass the randomization. Disabling the automatic notifications for some period implied that none of the declarations registered during that period were randomized by GasyNet, whether or not they were part of a corruption agreement.[53]

The evolution of the withholding of declarations from delegated randomization is depicted by the line with crosses in Figure 6 and is remarkably similar to the evolution of significant excess interaction. In fact, 36 percent of the declarations that were withheld are characterized by significant excess interaction. Conversely, 63 percent of the declarations characterized by significant excess interaction in the delegated randomization period were withheld from randomization. Interestingly, non-random assignment is persistent: for a given pairing of a broker with a particular inspector the share of withheld declarations is correlated with past deviations from random assignment, as shown in Appendix Table A5, suggesting the withholding of declarations from random assignment reflects a continuation of corruption agreements.

To ascertain that IT manipulation is driving the excess interaction we conduct a simple placebo test: we calculate the prevalence of excess interaction for the sub-sample of declarations that were randomized by GasyNet. Any excess interaction in this sub-sample should be purely accidental. Indeed, there is hardly any excess interaction in this sub-sample, as is shown by the line with rectangles for "random excess interaction" in Figure 6. The only period with some excess interaction is 5-7 months after the start of the delegated randomization intervention, when a number of inspectors went on repeated strikes (resulting in a higher average workload, and possibly higher excess interaction shares, for the remaining inspectors). Put differently, without the bypassing of the delegated randomization there would not have been a resurgence of excess interaction between inspectors and brokers. The patterns in Figure 6 are very similar when based on measures of excess interaction based on inspector-specific logit models, as shown in Appendix Figure A5.

9.2 Excess Interaction and Evasion Risk During Delegated Randomization Period

Declarations withheld from delegated randomization are not only characterized by significantly higher excess interaction shares but are also significantly more at risk of tax evasion on average than declarations that were

[53] The withholding of declarations subject to corruption agreements likely involves coordination between brokers and customs IT department staff: they are likely to agree on a particular time slot during which the delegated randomization is temporarily shut down and the declaration is registered. However other brokers, who are not part of corruption agreements may also register declarations during these time slots, which implies that not all declarations that are withheld from delegated randomization are part of corruption agreements.

randomized by GasyNet, as is shown in panel A of Table 6 which replicates some of the key specifications presented in Table 2 for the sample of withheld declarations. They are subject to tax rates that are 8.8 percent higher, have risk scores that are 1.2 points higher, are significantly heavier, and exhibit 19.7 percent lower initial unit prices relative to median import unit prices. These declarations exhibit 19.9 percent higher tax revenue losses than similar declarations whose assignment to inspectors was randomized by GasyNet. Random excess interaction (i.e., excess interaction in the sample of declarations whose assignment was randomized by GasyNet) is not correlated with declaration characteristics commonly associated with tax evasion, as is shown in panel B; all the R^2s are 0 and none of the coefficients are significant.

Even in the delegated randomization period, the excess interaction share is significantly correlated with declaration characteristics associated with tax evasion risk, as is shown in panel C which replicates Table 2 using the entire sample of declarations (randomized and withheld from randomization by GasyNet) in this period. However, these correlations are entirely driven by declarations withheld from randomization by GasyNet as is shown in panel D in which we interact the excess interaction share with the dummy for being withheld from randomization. While being withheld from randomization continues to significantly predict tax evasion risk, the excess interaction share only has predictive power when interacted with being withheld from randomization (consistent with the results in panel A). The declarations withheld from randomization and cleared by inspectors with a higher excess interaction share have significantly lower initial unit prices and significantly higher initial tax revenue losses (columns (20) and (21)). This suggests the declarations withheld from randomization by GasyNet that were targeted by corruption schemes were assigned to certain "preferred" inspectors.

9.3 Differential Treatment During Delegated Randomization Period

To evaluate the extent to which the IT manipulation during the delegated randomization period reflects a continuation of corruption, Table 7 examines whether inspectors treat the manipulated declarations differently. The table replicates the specifications in Table 3 but using different proxies for excess interaction.

Declarations that were withheld from delegated randomization are cleared significantly faster than declarations that were not, as is shown in panel A. The estimates also point to a reduced likelihood of being reported fraudulent and lower value and tax adjustments but these effects are not statistically significant. Declarations withheld from delegated randomization exhibit significant and substantial tax revenue losses of 17.5 percent on average, relative to other declarations, ceteris paribus.

Panel B shows that for the sub-sample of declarations randomized by GasyNet, random excess interaction does not predict how long inspectors take to clear goods, nor whether they will report the declaration as being fraudulent, or change the value or the tax yield. Random excess interaction is negatively correlated with tax revenue losses, suggesting that it is linked to lower, not higher, tax losses, in this sample of declarations randomized by GasyNet.

When we extend the sample by including withheld declarations, excess interaction is again associated with significantly accelerated clearance, significantly reduced fraud, lower value and tax adjustments and significantly higher tax revenue losses, as is shown in panel C. However this preferential treatment is driven by the declarations withheld from delegated randomization since we did not observe these correlations in the sample of declarations randomized by GasyNet analyzed in panel B.

In panel D we consider the entire sample of declarations and include the excess interaction share, a dummy for being withheld from delegated randomization, and the interaction between these two measures. The coefficients on the interaction term are consistently highly statistically significant. Preferential treatment is most pronounced for declarations that are withheld from delegated randomization and handled by inspectors who interact excessively frequently with a given broker. Such declarations are especially rapidly cleared, especially less likely to be deemed fraudulent, are subject to significantly lower value and tax adjustments, and, as a result, exhibit higher tax revenue losses.

The preferential treatment by inspectors of declarations characterized by excess interaction was thus enabled by manipulation of the IT system. Our placebo tests show clearly that when declarations are truly randomly assigned, there is hardly any excess interaction. Whatever accidental excess interaction nonetheless arises is not correlated with customs outcomes. By contrast, declarations withheld from delegated randomization are associated with excess interaction and an increased risk of tax evasion. They receive privileged treatment from inspectors, especially when such inspectors are handling a significantly larger share of a given broker's declarations than would be expected had the assignment of declarations followed official rules. All in all, these results corroborate our methodology to detect corruption and also attest to the difficulties associated with dislodging systemic corruption.

An event study of the impact of the delegated randomization on tax yield per declaration, shown in Appendix Figure A6, is consistent with this interpretation. Tax revenues increased significantly in the first few months of delegated randomization, but these gains were not sustained.[54]

Appendix Table A24 (panel B) presents estimates of the costs of corruption during the delegated randomization period, following a similar approach to that described in Section 7.[55] According to our preferred estimates which calculate hypothetical tax yield using prices reported by exporters, declarations that were likely the object of corruption - notably those withheld from randomization cleared by an inspector who interacted excessively frequently with the broker registering them - would have yielded an *additional*

[54]For the event study we use a sample including 6 months before and after the start of the delegated randomization and estimate an OLS regression of log 1 plus tax yield per declaration on dummies that define the position of the month relative to November 2017 as well as inspector, broker, source country, HS2-product, and calendar month fixed effects.

[55]We use estimates from regressions of hypothetical tax revenue losses on the excess interaction share, a dummy for declarations being withheld and their interaction shown in Appendix Table A23. Tax revenue in the absence of corruption is now calculated as $T^{NC} = T * exp(\widehat{\beta_E} * ES + \widehat{\beta_P} * WFR + \widehat{\beta_{EP}} * ES * WFR)$, where WFR is a dummy for declarations whithheld from randomization. The details on this calculation are shown in Appendix C.

11,223 USD in tax revenue. This represents a 129.8 percent increase over actual tax yield. Aggregate tax yield in this period would have been 2.6 percent higher had the randomization not been undermined by a new form of IT manipulation. These back-of-the-envelope estimates are crude and must be interpreted with caution given the difficulties inherent in measuring hypothetical tax yield and identifying deviant declarations.

10 Conclusion

Corrupt governance and limited state capacity to raise tax revenue constrain development, yet surprisingly little is known about the extent to which tax evasion is facilitated by (which) bureaucrats. Evidence on effectiveness of reforms to remedy institutionalized corruption is also limited. These questions are especially pertinent for customs agencies in low-income countries, which tend to be more reliant on tax revenues collected at the border than developed countries despite suffering higher levels of evasion.

This paper presents a new methodology to detect a specific form of corruption between customs inspectors and customs brokers, which we believe can be readily replicated in other contexts in which random assignment is used to deter corruption. Our approach is based on identifying deviations from random assignment of import declarations to inspectors that is prescribed by official rules. Such deviations result in excessively frequent pairing of brokers with the inspector(s) they are conspiring with.

Applying this methodology to Madagascar's main port of Toamasina unveiled that 10 percent of declarations were handled by inspectors that were not randomly assigned, plausibly because of manipulation of the IT system that assigns them. Non-randomly assigned declarations were shown to be subject to higher tax rates, have higher potential tax yield, higher risk scores, and lower unit prices than those reported for declarations containing the same goods. Non-random assignment is thus associated with higher tax revenue losses. Customs inspectors are shown to provide preferential treatment to these deviant declarations by clearing them faster, being less likely to require value, weight, and tax adjustments, and failing to identify fraud. Such corruption is costly; tax yield for non-randomly assigned declarations would have been 26 percent higher in the absence of excess interaction between inspectors and brokers. Overall tax revenues collected in Toamasina would have been 3 percent higher in the absence of the corruption scheme unveiled in this paper. These tax losses are very concentrated among a select few inspectors and brokers, whose propensity to engage in corruption increases with tenure in the port. Paradoxically, inspectors responsible for the largest tax revenue losses tend to collect more tax revenue per declaration, because they manage to control the assessment of the most lucrative declarations. Corruption is thus positively correlated with (naive) measures of tax revenue yield.

An intervention to curb corruption by having a third party randomize inspector assignment validates our methodology as it led to the temporary disappearance of excess interaction between inspectors and brokers. It also triggered a novel form of IT manipulation. While manipulation of inspector assignment was eventually weeded out with the help of improved IT infrastructure, our results serve as a reminder that technology is not a panacea in the fight against corruption. Rather, our results illustrate how IT solutions can be captured by bureaucrats and economic operators and serve as a conduit to corruption.

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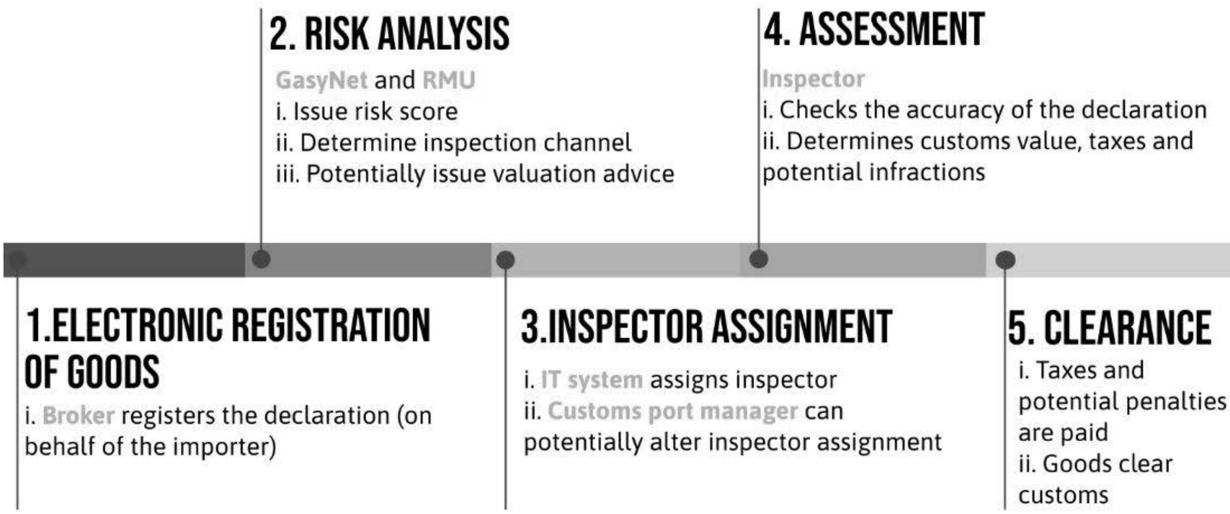
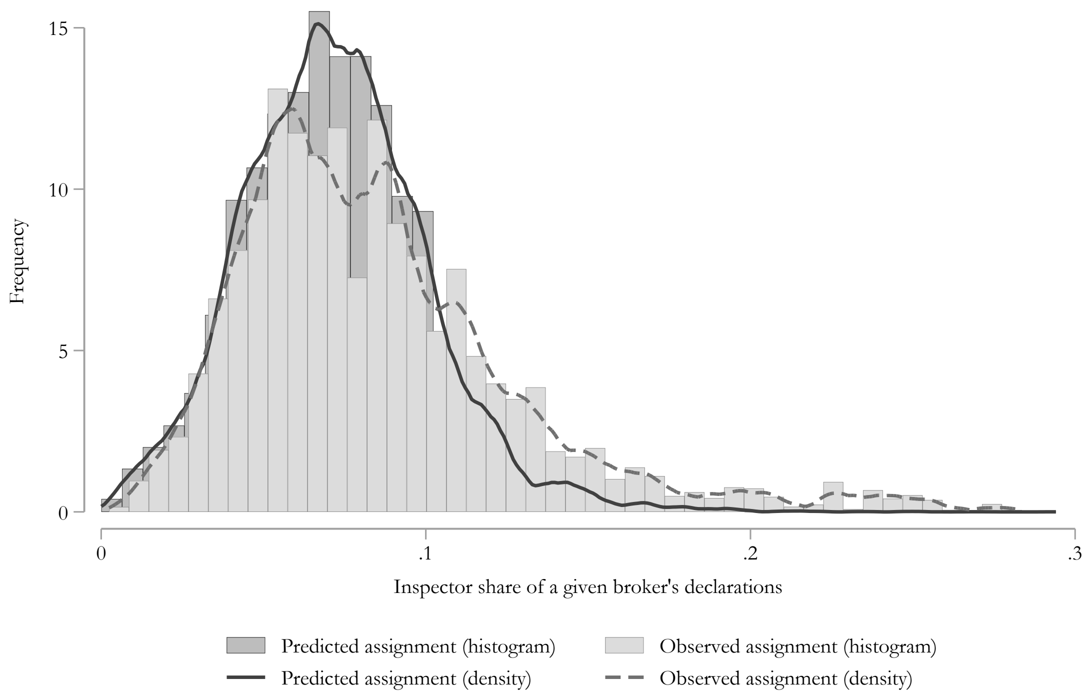
11 Tables and Figures

Figure 1: Stylistic Representation of the Clearance Process



Notes: The figure depicts a stylized representation of the customs clearance process. RMU is the risk management unit of customs. GasyNet is a third-party that assists customs with risk analysis and logistics.

Figure 2: Deviations from Official Rules in Assignment of Declarations to Inspectors

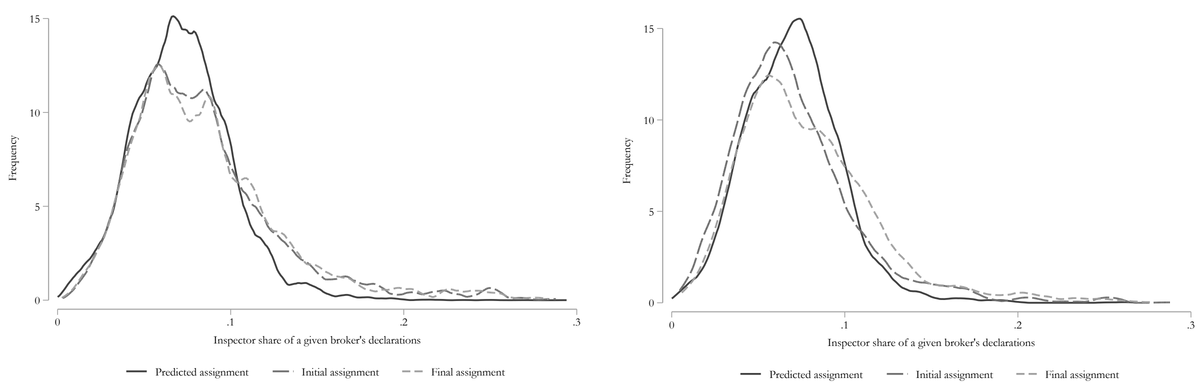


Notes: The figure shows the distribution of the share of declarations of a given broker handled by a given inspector in the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention). The darker-colored bars show the histogram of predicted inspection shares calibrated by setting the productivity of each inspector equal to the share of all declarations she handled in a given semester (see Section 4 for details), and the solid line the overlaid kernel density plot of such predicted inspection shares. The light-colored bars indicate the distribution of observed inspection shares, with the long-dashed line showing the overlaid kernel density plot.

Figure 3: Initial versus Final Inspector Assignment

a. All declarations

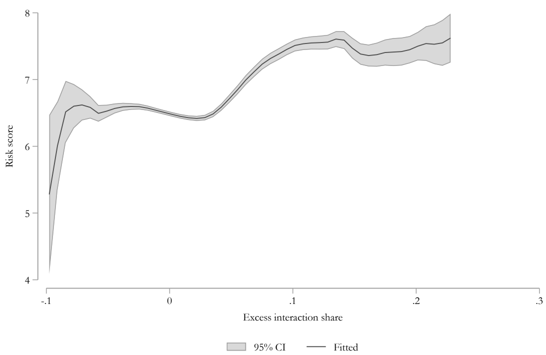
b. Declarations reassigned by customs port manager



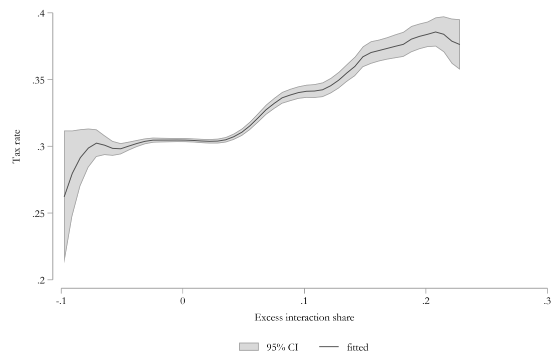
Notes: The figure shows the kernel density distributions of the share of declarations of a given broker handled by a given inspector in the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention). The solid density plot shows the distribution of predicted inspection shares calibrated by setting the productivity of each inspector equal to the share of all declarations she handled in a given semester (see Section 4 for details). The long-dashed line shows the distribution of the observed initial assignment of a declaration to a given inspector by the IT system (before the customs port manager potentially intervenes). The short-dashed line shows the distribution of the observed final assignment of a declaration to an inspector after potential re-assignments made by the customs port manager. In panel a the sample includes all declarations (both those that were re-assigned by the customs port manager and those that were not) while in panel b the sample includes only declarations that were re-assigned by the customs port manager.

Figure 4: Tax Evasion Risk and Excess Interaction

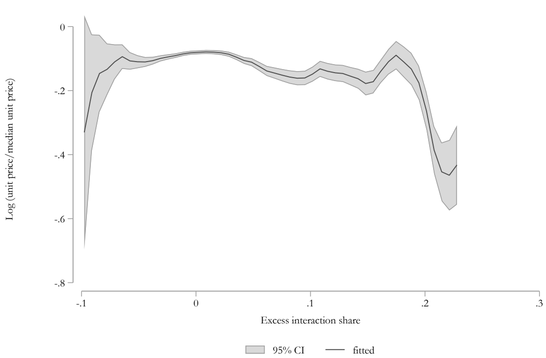
a. Risk Score



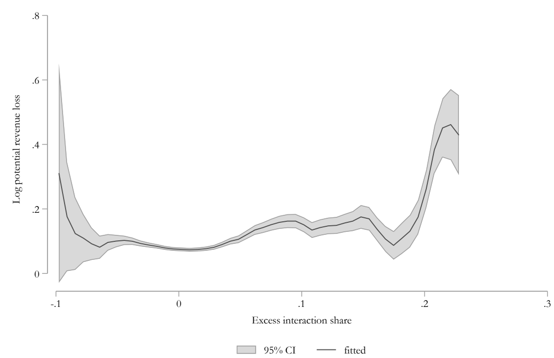
b. Tax Rate



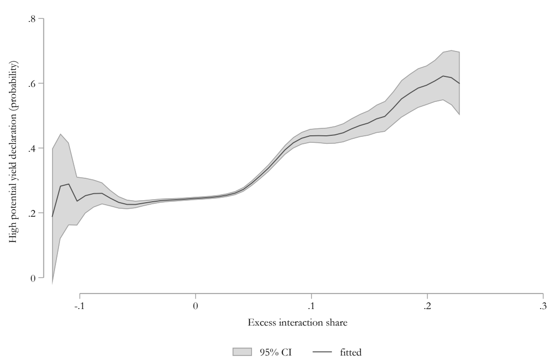
c. Log Initial Unit Price (Rel. to Internal Prices)



d. Initial Hypothetical Tax Revenue Losses



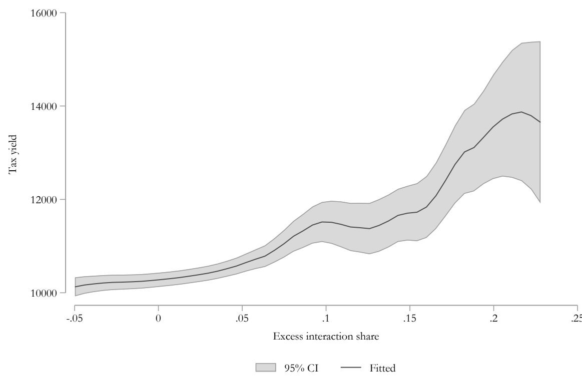
e. High Potential Tax Yield Dummy



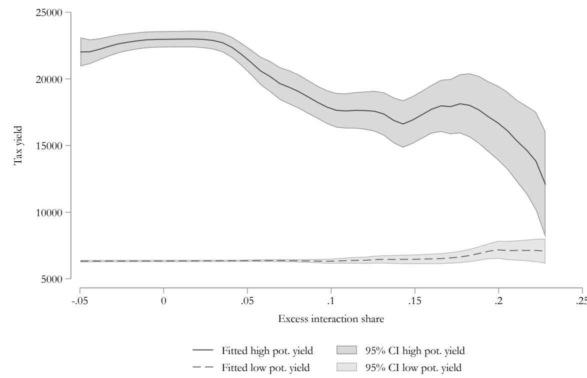
Notes: The graphs, generated using STATA 17, show weighted local polynomial plots (using the Epanechnikov kernel function) of a selected number of declaration characteristics capturing tax evasion risk on calibrated excess interaction shares for the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention). The sample used is the regression sample used to generate baseline results (see e.g. Table 3). *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). Initial hypothetical tax revenue losses refer to the tax revenue losses estimated based on internal reference prices. "high potential tax yield" declarations are those for which the hypothetical tax yield if the declaration was valued using external reference prices exceeds 20,000 USD. CI stands for confidence interval.

Figure 5: Tax Yield and Excess Interaction Share

a. All Declarations

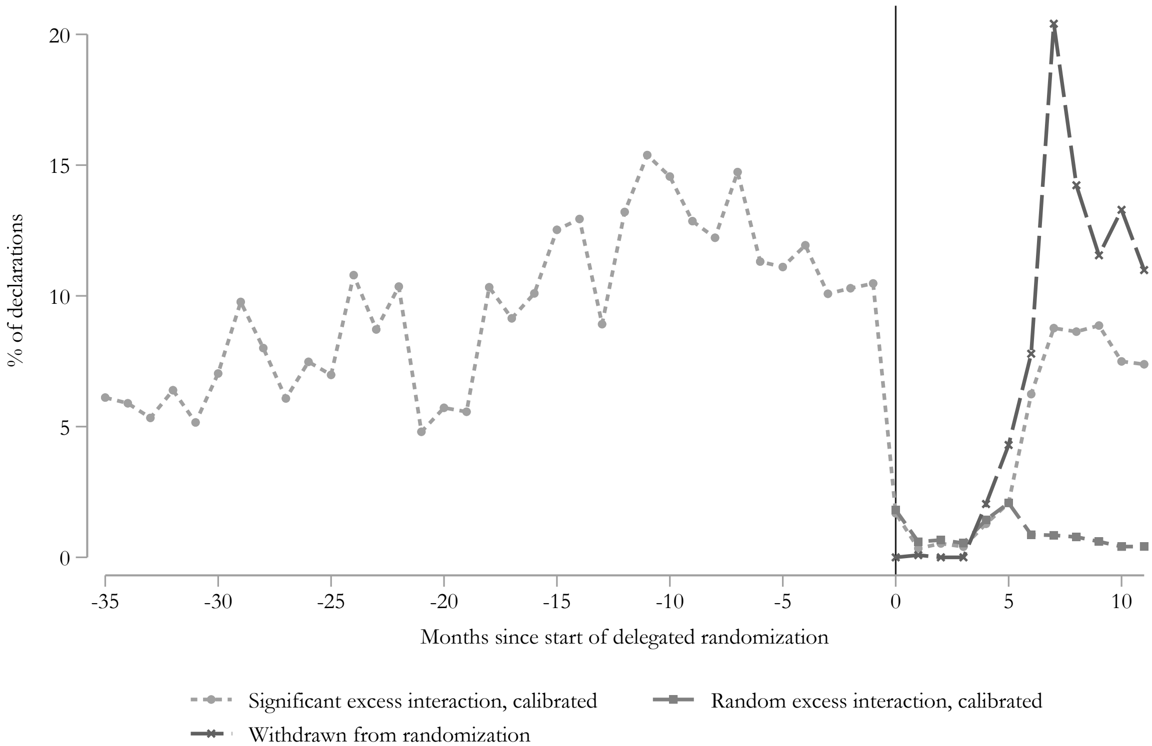


b. Heterogeneity by Potential Tax Yield



Notes: The graphs show weighted local polynomial plots (using the Epanechnikov kernel function) of the tax yield per declaration (in USD) on the share of declarations per inspector and semester that were subject to significant excess interaction (see section 4). Panel a combines all declarations whereas panel b distinguishes across "high potential yield" and "low potential yield" declarations. "high potential yield" ("low potential yield") declarations are those for which the hypothetical tax yield if the declaration was valued using external reference prices exceeds 20,000 USD (is less than 20,000 USD). The sample covers the period January 1, 2015 to November 17, 2017, (i.e., before the delegated randomization intervention).

Figure 6: Evolution of Non-Random Assignment



Notes: The line with circles "Significant excess interaction, calibrated" depicts the share of all import declarations that are characterized by significant excess interaction, calculated using calibration methods (as explained in Section 4). The vertical bar denotes the start of the delegated randomization intervention in which the assignment of declarations to inspectors was delegated to the third party GasyNet. Soon after this start, the customs IT department managed to withhold several declarations from the randomization process. The prevalence of these declarations is shown by the line with crosses "Withdrawn from randomization". The line with squares "Random excess interaction, calibrated" refers to the share of randomized declarations that are characterized by significant excess interaction, calculated using calibration methods. The sample covers the period January 1, 2015 to November 17, 2018.

Table 1: Prevalence of Excess Interaction (i.e., Non-Random Assignment)

Before delegated randomization of inspector assignment

A. Prevalence of excess interaction (i.e., non-random assignment) - calibrated

	Number	Number	%
	Non-randomly assigned	Total	
Declarations - after initial assignment	4,459	45,058	9.9%
Declarations - after final assignment	4,661	45,058	10.3%
Average per semester	At least one non-randomly assigned declaration	Total	
Inspectors	10	16	60.2%
Brokers	14	45	32.0%
Inspector-broker pairs	23	690	3.3%

B. Prevalence of excess interaction (i.e., non-random assignment) - inspector logits

	Number	Number	%
	Non-randomly assigned	Total	
Declarations - after initial assignment	4,800	45,058	10.7%
Declarations - after final assignment	4,545	45,058	10.1%
Average per semester	At least one non-randomly assigned declaration	Total	
Inspectors	10	16	61.2%
Brokers	15	45	34.2%
Inspector-broker pairs	25	690	3.6%
Average per semester	Broker fixed effects jointly significant	Total	
Inspectors - initial assignment	7	16	44.1%
Inspectors - final assignment	7	16	41.8%

Notes: Declarations are characterized by significant excess interaction if they are handled by an inspector whose *excess interaction share* (the difference between the share of given broker's declarations handled by the inspector in question and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules is positive and statistically significant (see Section 4). In panel A excess interaction measures are constructed using calibration methods. In panel B excess interaction measures are based on estimates from inspector-semester logit models. Initial assignment refers to the assignment originally made by the customs IT system. Final assignment takes into account subsequent potential re-assignment(s) made and therefore corresponds to the last assignment that selected the inspector that cleared the declaration. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table 2: Tax Evasion Risk and Excess Interaction

Before delegated randomization of inspector assignment						
Dependent variable:	**Risk score**	**Tax rate**	**Red channel dummy**	**Mixed shipment dummy**	**Differentiated share**	**Valuation advice dummy**
	(1)	(2)	(3)	(4)	(5)	(6)
Excess interaction share	5.178***	0.306***	0.088	0.775**	0.503**	0.937***
	(1.051)	(0.064)	(0.240)	(0.336)	(0.186)	(0.330)
Observations	44,522	45,058	45,058	45,058	45,058	45,058
R-squared	0.006	0.010	0.000	0.005	0.002	0.019
Dependent variable:		**Log initial value**	**Log initial weight**	**Log initial unit price (relative to internal prices)**	**Initial hyp. tax rev. losses**	**High potential tax yield dummy**
		(7)	(8)	(9)	(10)	(11)
Excess interaction share		0.256	1.457***	-0.591**	0.632**	1.540***
		(0.358)	(0.503)	(0.243)	(0.240)	(0.235)
Observations		45,058	45,058	45,033	45,033	31,402
R-squared		0.000	0.001	0.002	0.003	0.020

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table 3: Differential Treatment by Inspectors

Before delegated randomization of inspector assignment					
Dependent variable	**Time**	**Fraud**	**Δlog value**	**Δlog tax**	**Hyp. tax revenue losses**
	(1)	(2)	(3)	(4)	(5)
Excess interaction share	-2.008***	-0.275**	-0.079***	-0.086***	0.389**
	(0.361)	(0.101)	(0.022)	(0.031)	(0.175)
Declaration characteristics	Yes	Yes	Yes	Yes	Yes
Inspector fixed effects	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.318	0.214	0.152	0.132	0.211
P-value joint significance of broker fixed effects	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). Declarations characteristics include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table 4: Alternative Explanations for Differential Treatment

Before delegated randomization of inspector assignment					
Dependent variable	**Time**	**Fraud**	**Δlog value**	**Δlog tax**	**Hyp. tax revenue losses**
A. Controlling for familiarity					
	(1)	(2)	(3)	(4)	(5)
Excess interaction share	-1.797***	-0.278***	-0.081***	-0.082***	0.323*
	(0.429)	(0.096)	(0.023)	(0.028)	(0.176)
Familiarity	-0.042	-0.000	0.000	-0.001	0.012*
	(0.027)	(0.005)	(0.002)	(0.001)	(0.006)
Observations	40,990	44,359	44,273	40,324	44,335
R-squared	0.321	0.214	0.153	0.133	0.211
B. Controlling for congestion					
	(6)	(7)	(8)	(9)	(10)
Excess interaction share	-2.002***	-0.275**	-0.079***	-0.085***	0.389**
	(0.362)	(0.100)	(0.022)	(0.031)	(0.175)
Congestion	0.098**	-0.004	0.001	0.000	-0.001
	(0.038)	(0.004)	(0.001)	(0.001)	(0.005)
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.318	0.214	0.152	0.132	0.211
C. Excluding declarations registered outside regular business hours					
	(11)	(12)	(13)	(14)	(15)
Excess interaction share	-2.033***	-0.270***	-0.079***	-0.088***	0.385**
	(0.358)	(0.093)	(0.021)	(0.028)	(0.177)
Observations	40,285	43,497	43,409	39,534	43,473
R-squared	0.316	0.220	0.156	0.136	0.210
D. Adding importer fixed effects					
	(16)	(17)	(18)	(19)	(20)
Excess interaction share	-2.051***	-0.170**	-0.069***	-0.081***	0.242***
	(0.287)	(0.071)	(0.021)	(0.024)	(0.087)
Observations	40,311	43,691	43,601	39,678	43,669
R-squared	0.393	0.327	0.292	0.297	0.429
E. Adding importer fixed effects and excess interaction share with importers					
	(21)	(22)	(23)	(24)	(25)
Excess interaction share	-2.056**	-0.221*	-0.047	-0.075*	0.092
	(0.837)	(0.122)	(0.035)	(0.040)	(0.166)
Excess interaction share with importer	-0.172	0.016	-0.003	0.006	0.099
	(0.474)	(0.104)	(0.018)	(0.027)	(0.105)
Observations	9,537	10,281	10,263	9,184	10,278
R-squared	0.371	0.308	0.238	0.226	0.240
F. Dropping top 3 inspectors with the largest share of declarations with excess interaction each semester					
	(26)	(27)	(28)	(29)	(30)
Excess interaction share	-2.207***	-0.258***	-0.085***	-0.087***	0.367*
	(0.432)	(0.082)	(0.022)	(0.029)	(0.180)
Observations	32,542	35,222	35,152	31,935	35,203
R-squared	0.322	0.222	0.161	0.141	0.201

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). All specifications control for the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, a dummy indicating the declaration was subject to valuation advice, inspector fixed effects, broker fixed effects, source country fixed effects, and month-year fixed effects. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table 5: Concentration of Tax Revenue Losses by Semester

Rank per semester	**Total taxes collected** average per semester (USD)	**Tax losses** average per semester (USD)	**% total taxes collected** per semester	**% total tax losses** per semester
		Panel A: By inspector (ranked in terms of tax revenue losses, from largest to smallest, by semester)		
Inspector rank (in a given semester)				
1	6,491,683	677,109	8.2%	32.8%
2	6,552,940	499,588	8.0%	22.4%
3	5,901,505	324,983	7.2%	13.4%
4	5,663,769	265,376	7.3%	10.5%
5	4,890,071	180,883	6.1%	7.4%
Rank 6-10 (combined)	25,181,080	347,773	31.2%	13.4%
Rank 11 and higher (combined)	23,764,220	5,242	31.9%	0.2%
Average per inspector per semester	4,802,772	140,875	6.1%	6.1%
		Panel B: By broker (ranked in terms of tax revenue losses, from largest to smallest, by semester)		
Broker rank (in a given semester)				
1	1,734,389	514,420	2.3%	24.2%
2	3,294,547	353,191	4.0%	16.2%
3	2,237,922	288,914	2.7%	12.7%
4	3,059,864	239,310	4.0%	10.6%
5	3,671,714	186,521	4.8%	7.7%
Rank 6-10 combined	11,782,51	535,779	15.1%	22.0%
Rank 10-20 (combined)	13,552,180	182,819	17.1 %	6.5%
Rank 21 and higher (combined)	39,112,140	0,000	50.1%	0.0%
Average by broker per semester	1,749,709	51,322	2.2%	2.2%
		Panel C: Overall		
Total per semester	78,445,268	2,300,954	100%	2.9%

Notes: Tax losses are calculated as the difference between the counterfactual tax yield collected in the absence of significant excess interaction and actual tax yield. Counterfactual tax yield is calculated using external reference prices (see section 3) taking into consideration underreporting of quantities (see section 7 for details). Inspectors (brokers) are ranked each semester on the basis of their total tax revenue losses (with rank 1 denoting the inspector with the highest tax losses), with ties arbitrarily split in the case of non-participation in the scheme (we assume that inspectors (brokers) that do not participate in the scheme do not contribute to tax losses associated with the scheme). To avoid having these arbitrary splits impact the rankings we assign to each of the non-participating inspectors the average tax yield of inspectors (brokers) that did not participate in the scheme that semester. This effectively amounts to calculating the average over all possible permutations of randomly assigned splits in the case of tiebreaks. The statistics in this table reflect averages across semesters (note that it is possible for a different inspector or broker to assume rank 1 in different semesters). The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table 6: Tax Evasion Risk and Excess Interaction During Delegated Randomization

	During delegated randomization of inspector assignment					
Dependent variable:	**Excess interaction share**	**Tax rate**	**Risk score**	**Log initial weight**	**Log initial unit price (relative to internal prices)**	**Initial hyp. tax revenue losses**
	A. Withheld from randomization					
	(1)	(2)	(3)	(4)	(5)	(6)
Withheld from randomization (WFR)	0.064**	0.088***	1.173***	0.160	-0.197***	0.199***
	(0.026)	(0.010)	(0.222)	(0.117)	(0.061)	(0.061)
Observations	17,736	17,738	17,169	17,738	17,728	17,728
R-squared	0.153	0.026	0.011	0.001	0.011	0.012
	B. Excess interaction - delegated randomized declarations only					
		(7)	(8)	(9)	(10)	(11)
Random excess interaction share		0.083	-0.024	-0.302	0.076	-0.078
		(0.173)	(2.316)	(1.251)	(0.169)	(0.158)
Observations		16,461	15,925	16,461	16,454	16,454
R-squared		0.000	0.000	0.000	0.000	0.000
	C. Excess interaction					
		(12)	(13)	(14)	(15)	(16)
Excess interaction share		0.307***	4.212**	0.392	-0.840**	0.836**
		(0.084)	(1.360)	(0.844)	(0.311)	(0.312)
Observations		17,736	17,167	17,736	17,726	17,726
R-squared		0.008	0.004	0.000	0.005	0.006
	D. Combined measures					
		(17)	(18)	(19)	(20)	(21)
Withheld from randomization (WFR)		0.079***	1.015***	0.177	-0.110***	0.114***
		(0.009)	(0.234)	(0.139)	(0.032)	(0.033)
Excess interaction share		0.093	1.196	0.147	0.032	-0.032
		(0.094)	(1.609)	(1.251)	(0.104)	(0.098)
WFR*Excess interaction share		0.051	1.169	-0.386	-1.286***	1.262***
		(0.067)	(2.000)	(1.531)	(0.327)	(0.325)
Observations		17,736	17,167	17,736	17,726	17,726
R-squared		0.027	0.011	0.001	0.015	0.016

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. WFR stands for withheld from randomization. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). *Random excess interaction share* is the excess interaction share calculated using only the set of declarations that were not withheld from randomization. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period November 18, 2017 to November 17, 2018 (i.e. the period of the delegated randomization intervention).

Table 7: Differential Treatment During Delegated Randomization

	During delegated randomization of inspector assignment				
Dependent variable:	**Time**	**Fraud**	**Δ log value**	**Δ log tax**	**Hyp. tax revenue losses**
A. Withheld from randomization					
	(1)	(2)	(3)	(4)	(5)
Withheld from randomization (WFR)	-0.853***	-0.015	-0.003	-0.003	0.175***
	(0.114)	(0.020)	(0.005)	(0.005)	(0.032)
Observations	16,455	17,169	17,147	15,188	17,159
R-squared	0.239	0.389	0.271	0.250	0.191
B. Random excess interaction share - delegated randomized declarations only					
	(6)	(7)	(8)	(9)	(10)
Random excess interaction share	-0.193	-0.031	-0.002	0.005	-0.287*
	(0.716)	(0.138)	(0.031)	(0.039)	(0.151)
Observations	15,899	15,925	15,907	13,692	15,918
R-squared	0.227	0.394	0.275	0.259	0.164
C. Excess interaction share					
	(11)	(12)	(13)	(14)	(15)
Excess interaction share	-2.352***	-0.187**	-0.051*	-0.038	0.421**
	(0.600)	(0.069)	(0.025)	(0.027)	(0.150)
Observations	16,453	17,167	17,145	15,186	17,157
R-squared	0.232	0.390	0.271	0.250	0.185
D. Excess interaction share and declarations withheld from randomization (and their interaction)					
	(16)	(17)	(18)	(19)	(20)
Excess interaction share	-0.639***	0.007	0.004	0.002	0.129***
	(0.113)	(0.019)	(0.005)	(0.006)	(0.027)
Withheld from randomization (WFR)	-1.060*	-0.075	-0.014	-0.012	-0.097
	(0.522)	(0.078)	(0.021)	(0.023)	(0.101)
WFR*Excess interaction share	-2.542**	-0.370**	-0.128**	-0.083*	0.956**
	(0.899)	(0.124)	(0.043)	(0.046)	(0.303)
Observations	16,453	17,167	17,145	15,186	17,157
R-squared	0.241	0.390	0.272	0.250	0.192

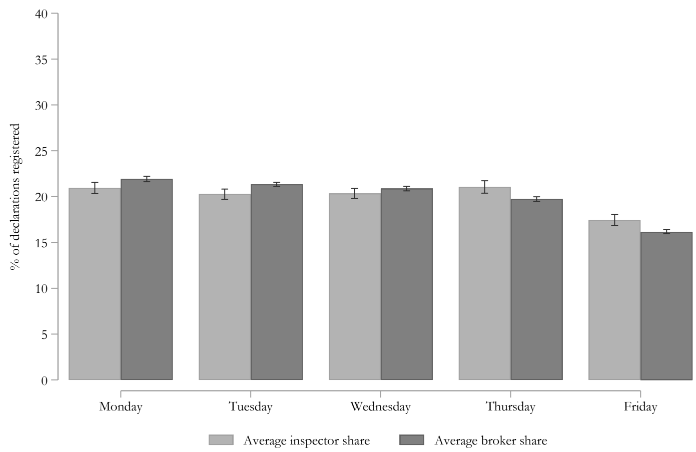
Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. WFR stands for withheld from randomization. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). *Random excess interaction share* is the excess interaction share calculated using only the set of declarations that were not withheld from randomization. "Observations" refers to the number of non-singleton observations. All specifications control for the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice, inspector fixed effects, broker fixed effects, source country fixed effects, and month-year fixed effects. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period November 18, 2017 to November 17, 2018 (i.e. the period of the delegated randomization intervention).

Appendix (for Online Publication Only)

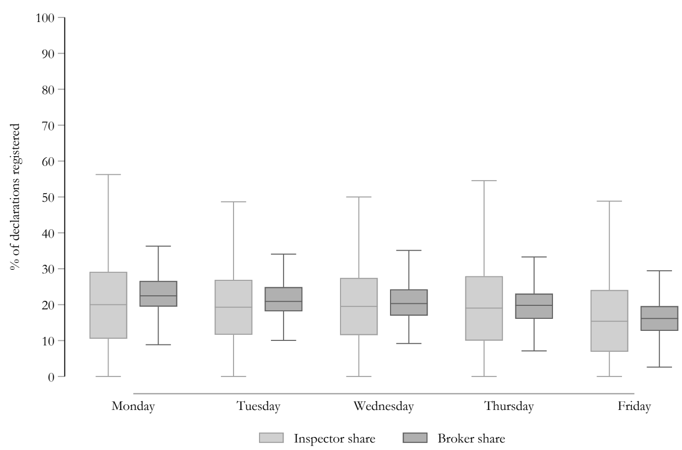
A Additional Tests

Figure A1: Fluctuations in Inspectors' and Brokers' Caseload

a. Fluctuations in caseload

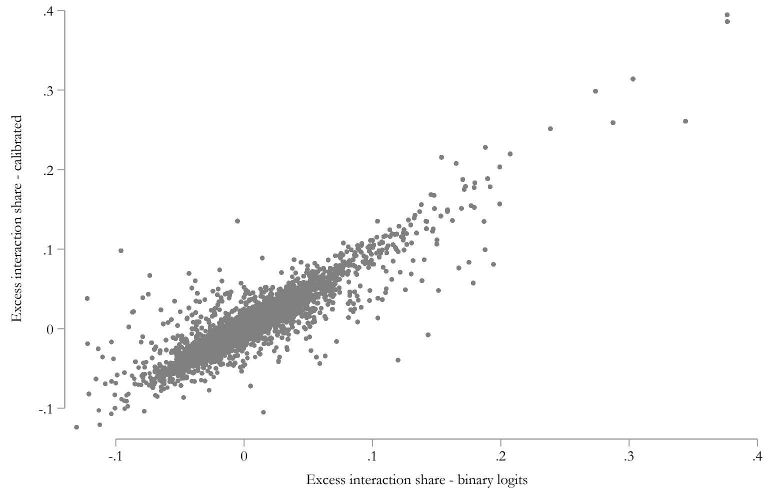


b. Average Daily Shares



Notes: The graphs show the distribution of caseload across weekdays for both brokers and inspectors. An inspector (a broker) is defined to work on a given weekday if she assesses (registers) at least one declaration on that weekday. For inspectors, panel a plots the average weekly shares of declarations they cleared on a particular weekday, while panel b plots the distribution of such shares (not averaging by inspector). For brokers, panel a plots the average weekly shares of declarations they registered on a particular weekday while panel b plots the distribution of such shares (not averaging by broker). The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

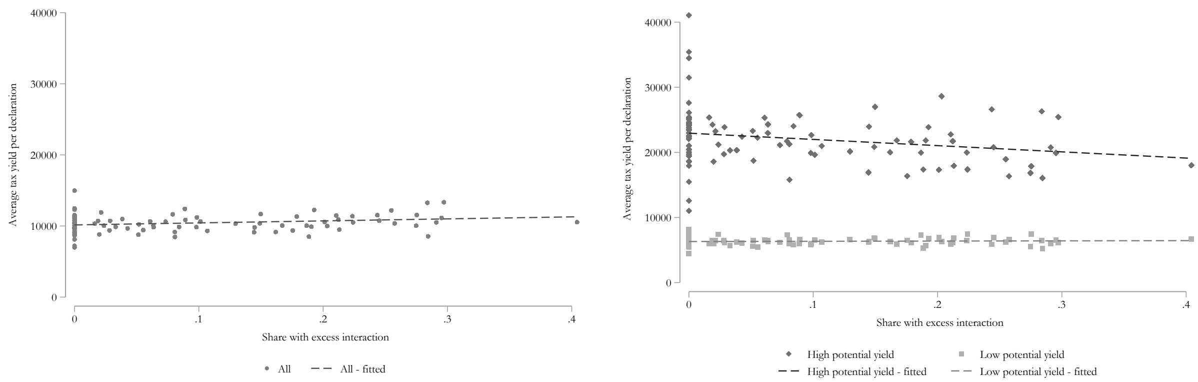
Figure A2: Correlation Between Alternative Measures of Excess Interaction



Notes: In the vertical axis excess interaction share measures are constructed using calibration methods. In the horizontal axis excess interaction share measures are based on estimates from inspector-semester logit models. The sample used is the regression sample used to generate baseline results (see e.g. Table 3). It covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Figure A3: Average Tax Yield and Excess Interaction by Inspector-Semester

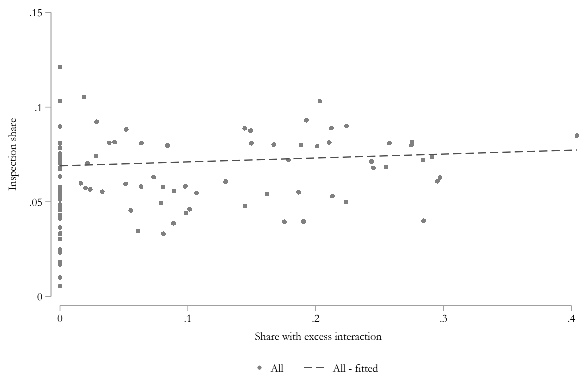
a. All Declarations b. Heterogeneity by Potential Tax Yield



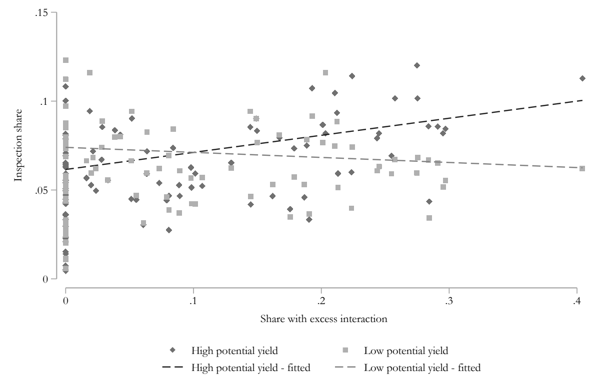
Notes: The graphs plot the tax yield per declaration averaged by inspector-semester against the share of declarations by inspector-semester that were subject to significant excess interaction (see section 4). Panel a shows averages calculated over all declarations whereas panel b distinguishes across averages for "high potential yield" and for "low potential yield" declarations. "high potential yield" ("low potential yield") declarations are those for which the hypothetical tax yield if the declaration was valued using external reference prices exceeds 20,000 USD (is less than 20,000 USD). The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Figure A4: Average Inspection Shares and Excess Interaction by Inspector-Semester

a. All Declarations

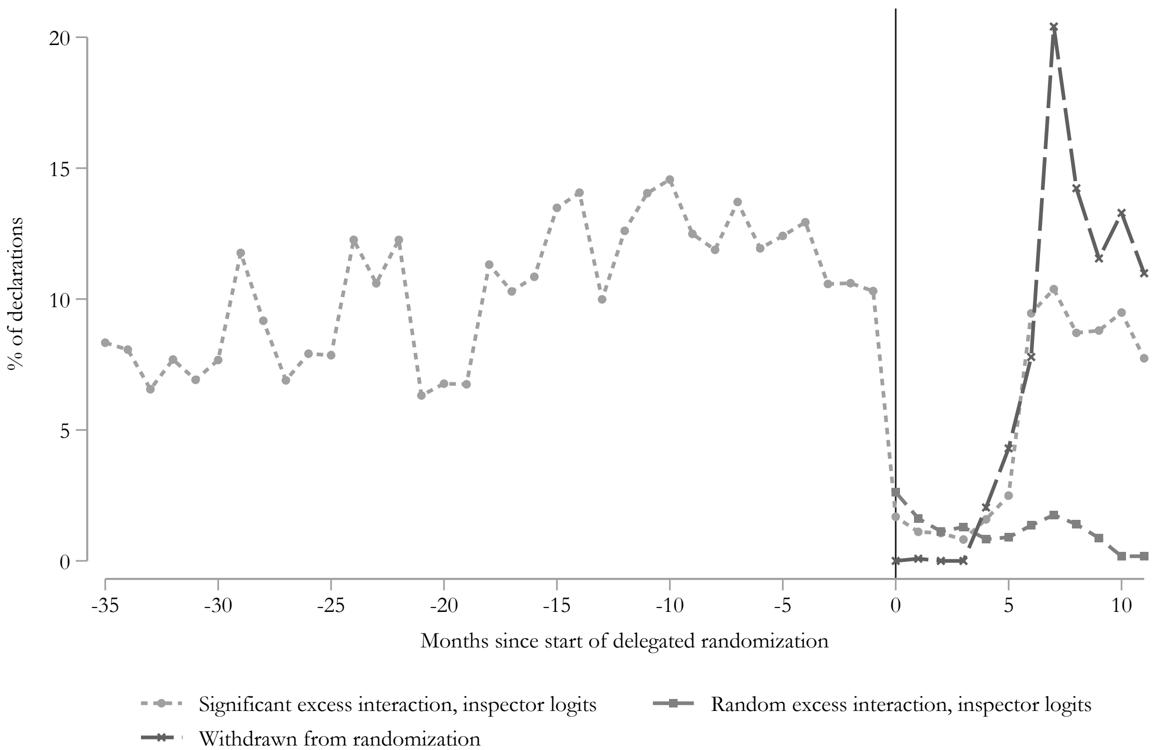


b. Heterogeneity by Potential Tax Yield



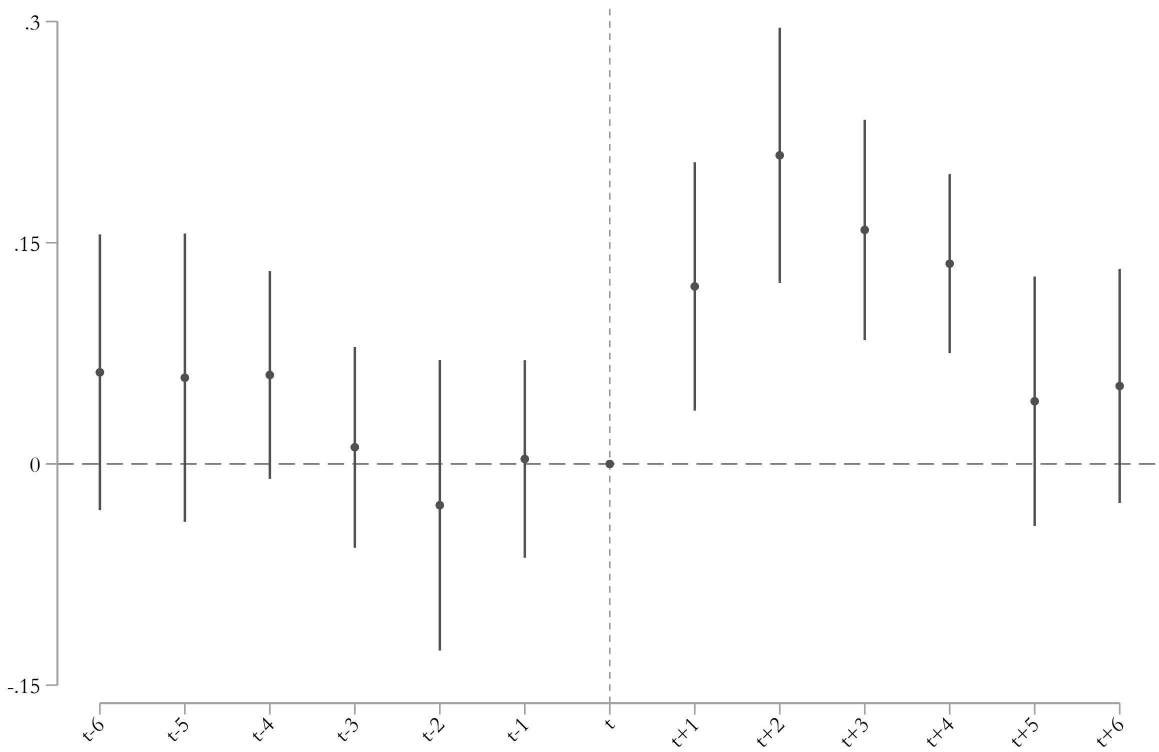
Notes: The graphs plot the inspection share by inspector-semester against the share of declarations by inspector-semester that were subject to significant excess interaction (see section 4). Panel a shows averages calculated over all declarations whereas panel b distinguishes across averages for "high potential yield" and for "low potential yield" declarations. "high potential yield" ("low potential yield") declarations are those for which the hypothetical tax yield if the declaration was valued using external reference prices exceeds 20,000 USD (is less than 20,000 USD). The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Figure A5: Evolution of Non-Random Assignment - Inspector-Specific Logit Models



Notes: The line with circles "Significant excess interaction, inspector logits" depicts the share of all import declarations that are characterized by significant excess interaction, calculated using inspector-specific binomial logit models (as explained in Section 4). The vertical bar denotes the start of the delegated randomization intervention in which the assignment of declarations to inspectors was delegated to the third party GasyNet. Soon after this start, the customs IT department managed to withhold several declarations from the randomization process. The prevalence of these declarations is shown by the line with crosses "Withdrawn from randomization". The line with squares "Random excess interaction, inspector logits" refers to the share of randomized declarations that are characterized by significant excess interaction, calculated using using inspector-specific binomial logit models. The sample covers the period January 1, 2015 to November 17, 2018.

Figure A6: Impact of Delegated Randomization on Tax Yield - Event Study



Notes: The graph presents the estimates from an event study of the impact of the introduction of the delegated randomization on tax yield per declaration. Month t denotes the start of the delegated randomization and the sample covers 6 months before and 6 months after the start of the delegated randomization on November 18 2017. An OLS regression of log 1 plus tax yield per declaration is estimated on dummies that define the position of the month relative to November 2017 as well as inspector, broker, source country, HS2-product, and calendar month fixed effects. Standard errors are clustered by inspector. The dots represent the point estimates and the vertical bars the 95 % confidence interval.

Table A1: Variable Definitions, 1/5

Variable name	Variable definition and data source(s)
A. Additional control variables	
Familiarity	Log of 1 plus the number of declarations registered by a given broker and cleared by a given inspector in the six preceding months. Defined at the inspector-broker-semester level. Source: Madagascar customs.
Congestion	Log of the number of declarations assigned to the inspector in a given month. Defined at the inspector-month level. Source: Madagascar customs.
B. Auxiliary variables	
Internal reference prices (IRP)	Median of unit prices (ratio of value to quantity in kilograms) of a given HS 6-digit product from a given country of origin computed across all import declarations in Madagascar customs data in each year. Defined at the country-HS 6-digit product-year level. Source: Madagascar customs.
Initial [final] average internal reference price	Weighted average of the IRP for all items included in the import declaration with weights being the initially submitted weights by the importer or his representative [final weights retained by customs] for each item. Defined at the declaration level. Source: Madagascar customs.
External reference prices (ERP)	Unit price (ratio of value to quantity in kilograms) of a given product being exported by a given trading partner to Madagascar. Defined at the country-HS 6-digit product-year level. Source: UN COMTRADE.
Initial [final] average external reference price	Weighted average of the ERP for all items included in the import declaration with weights being the initially submitted weights by the importer or his representative [final weight retained by customs] for each item. Defined at the declaration level. Sources: Madagascar customs and UN COMTRADE.
C. Broker characteristics	
Based in Toamasina	Dummy variable that takes value 1 if the broker's headquarters are located in Toamasina, and 0 otherwise. Defined at the broker level. Source: Madagascar customs.
Average market share	Average share of declarations registered in Toamasina handled by the broker across semesters. Defined at the broker level. Source: Madagascar customs.
Importer acting as own broker	Dummy variable that takes value 1 if the broker serves only one importer (itself), and 0 otherwise. Defined at the broker level. Source: Madagascar customs.
Tenure >5-10 years	Dummy variable that takes value 1 if the broker was active in Toamasina at least 5 and fewer than 10 years, and 0 otherwise. Defined at the broker level. Source: Madagascar customs.
Tenure 10 plus years	Dummy variable that takes value 1 if the broker was active in Toamasina for more than 10 years, and 0 otherwise. Defined at the broker level. Source: Madagascar customs.
D. Corruption proxies	
Excess interaction share	Difference between the observed share of a given broker's declarations handled by an inspector in a given semester and the hypothetical share the inspector would be expected to handle if the declarations were conditionally randomly assigned (predicted using a multinomial distribution that should govern the assignment of import declarations to inspectors if official rules were adhered to as explained in Section 4). Defined at the inspector-broker-semester level. Source: Madagascar customs.

Table A1: Variable Definitions, 2/5

Variable name	Variable definition and data source(s)
D. Corruption proxies, continued	
Excess interaction share - inspector logits	Difference between the share of given broker's declarations handled by an inspector in a given semester predicted by a binomial logit model that includes risk controls, day of week and broker fixed effects, and the share predicted by a binomial logit model that includes only day of week fixed effects (that capture conditional random assignment accommodating variation in inspectors' schedules).Defined at the inspector-broker-semester level. Source: Madagascar customs.
Significant excess interaction indicator	Dummy variable that takes value 1 if the excess interaction share is positive and statistically significant, i.e., if an inspector handles a much higher share of a given broker's declarations in a given semester than would be expected if official rules were adhered to, where statistical significance is based on simulation methods (discussed in Section 4), and 0 otherwise. Defined at the inspector-broker-semester level. Source: Madagascar customs.
Significant excess interaction indicator - inspector logits	Dummy variable that takes value 1 if the relevant broker fixed effect in the binomial logit model of the assignment of declarations that controls for day of week dummies, risk controls, and broker fixed effects is significant at the 1% significance level, and 0 otherwise. Defined at the inspector-broker-semester level. Source: Madagascar customs.
Withheld from randomization	Dummy variable that takes value 1 if the random assignment of the declaration was not performed by third-party GasyNet even though it was supposed to, and 0 if it was. Defined at the declaration level. Source: GasyNet.
Inspection share	Inspector's share of all import declarations cleared in Toamasina in a given semester. Source: Madagascar customs.
E. Customs outcomes	
Time	Log of the difference in time (measured in hours) between the date of assessment of the declaration by the inspector and the date of assignment of the declaration to the inspector that cleared the declaration. Defined at the declaration level. Source: Madagascar customs.
Fraud	Dummy variable that takes value 1 if the customs inspector identifies fraud in the import declaration and 0 otherwise. Defined at the declaration level. Source: Madagascar customs.
Δ log value	Difference between the log of the declaration value retained by customs and the log of the initially submitted value by the importer or his representative. Defined at the declaration level. Source: Madagascar customs.
Δ log tax	Difference between the log of the taxes paid (including tariffs, VAT) on the declaration and the log of taxes that should have been paid in the absence of customs controls (which equal taxes paid minus tax adjustment by the customs inspector). Defined at the declaration level. Source: Madagascar customs.
Tax yield	Sum of total taxes assessed (in USD). Defined at the declaration level. Source: Madagascar customs.
Hypothetical tax revenue losses (internal prices)	Computed as log (1+ (tax rate $\times$ final average internal reference price $\times$ final weight retained by customs)) - log (1 + (tax rate $\times$ final value retained by customs)). Defined at the declaration level. Source: Madagascar customs.
Δ log weight	Difference between the log of the final weight retained by customs and the log of the initially submitted weight by the importer or his representative. Defined at the declaration level. Source: Madagascar customs.
Weight gap (relative to port authority weight)	Difference between the log of the port authority weight and the log of the initially submitted weight by the importer or his representative. Defined at the declaration level. Source: Madagascar customs and Madagascar International Container Terminal Services Limited (MICTSL).
Hypothetical tax revenue losses (internal prices & port authority weight)	Computed as log (1+ (tax rate $\times$ final average internal reference price $\times$ port authority weight)) - log (1 + (tax rate $\times$ final value retained by customs)). Defined at the declaration level. Source: Madagascar customs and MICTSL.

Table A1: Variable Definitions, 3/5

Variable name	Variable definition and data source(s)
E. Customs outcomes, continued	
Hypothetical tax revenue losses (external reference prices)	Computed as log (1+ (tax rate $\times$ average final external reference price $\times$ final weight retained by customs)) - log (1 + (tax rate $\times$ final value retained by customs)). Defined at the declaration level. Sources: Madagascar customs and UN COMTRADE.
Hypothetical tax revenue losses (external reference prices & port authority weight)	Computed as log (1+ (tax rate $\times$ average final external reference price $\times$ port authority weight)) - log (1 + (tax rate $\times$ final value retained by customs)). Defined at the declaration level. Sources: Madagascar customs, MICTSL and UN COMTRADE.
Hypothetical tax revenue losses (valuation advice)	Computed as log (1+ (tax rate $\times$ reference value F.O.B. suggested by third-party GasyNet)) - log (1 + (tax rate $\times$ final value retained by customs)). Defined at the declaration level. Sources: Madagascar customs and GasyNet.
F. *Ex-ante* risk characteristics & other characteristics of declarations	
Tax rate	Sum of taxes (including tariffs as well as Value Added Taxes) that have to be paid divided by the import value retained by customs. Defined at the declaration level. Source: Madagascar customs.
Risk score	Score calculated by GasyNet that indicates the risk of tax evasion for the import declaration ranging from 1 (very low risk) to 9 (very high risk). Defined at the declaration level. Source: GasyNet.
Red channel dummy	Dummy variable that takes value 1 if the customs risk management system routed the declaration to the frontline inspection channel (red channel) and 0 otherwise. Defined at the declaration level. Source: Madagascar customs.
Mixed shipment dummy	Dummy variable that takes value 1 if the import declaration includes more than 1 HS 6-digit product and 0 otherwise. Defined at the declaration level. Source: Madagascar customs.
Differentiated share	Share of HS 6-digit products in the import declaration that are defined as differentiated according to the conservative classification by Rauch (1999). Defined at the declaration level. Source: Rauch (1999) and a concordance between HS 6-digit revision 2012 classification and SITC revision 2 classification from UN COMTRADE.
Valuation advice dummy	Dummy variable that takes value 1 if GasyNet provided a valuation advice for this import declaration and 0 otherwise. Defined at the declaration level. Source: GasyNet.
Log initial value	Log of the initially declared import value in USD (converted from Ariary using monthly exchange rates calculated as an average of daily exchange rates from the Central Bank of Madagascar). Defined at the declaration level. Source: Madagascar customs.
Log initial weight	Log of the initially declared total weight (in kilograms). Defined at the declaration level. Source: Madagascar customs.
Log port authority weight	Log of the sum of the weight of all containers used to ship the goods included in the import declaration measured at the port upon arrival (in kilograms). Defined at the declaration level (for containerized declarations). Source: Madagascar International Container Terminal Services Limited (MICTSL).
Log initial unit price (relative to internal prices)	Difference between the log of the initial average internal reference price of the declaration and the log of the initially submitted unit price by the importer or his representative (defined as the weighted average of the unit prices (values divided by weights) for all items included in the import declaration, with weights being the initially submitted weights for each item). Defined at the declaration level. Source: Madagascar customs.
Initial hypothetical tax revenue losses (internal prices)	Computed as log(1+ (total taxation rate $\times$ initial average internal reference price $\times$ initially submitted weight by the importer or his representative))-log(1 + (total taxation rate $\times$ initially submitted value by the importer or his representative)). Defined at the declaration level. Source: Madagascar customs.

Table A1: Variable Definitions, 4/5

Variable name	Variable definition and data source(s)
F. *Ex-ante* risk characteristics & other characteristics of declarations, continued	
Trade elasticity (Broda and Weinstein, 2006)	Weighted average trade elasticity of the items (i.e., products) included in the declaration using elasticity estimates of Broda and Weinstein (2006) at the HS 3-digit level, with weights corresponding to the share of the total import value each item accounts for. Defined at the declaration level. Source: Broda and Weinstein (2006) and Madagascar customs.
Trade elasticity (Fontagne et al. 2022)	Weighted average trade elasticity of items (i.e., products) included in the declaration using elasticity estimates of Fontagne et al. (2022) at the HS 6-digit level, with weights corresponding to the share of the total import value each item accounts for. Defined at the declaration level. Source: Fontagne et al. (2022) and Madagascar customs
Relationship stickiness (Martin et al. 2020)	Weighted average relationship stickiness of items (i.e., products) included in the declaration using the measures of Martin et al. (2020) at the HS 6-digit level, with weights corresponding to the share of the total import value each item accounts for. Defined at the declaration level. Source: Martin et al. (2020) and Madagascar customs
High potential tax yield dummy	Dummy variable that takes value 1 if the hypothetical tax burden associated with valuing the declaration using external reference prices exceeds 20,000 USD. Defined at the declaration level. Source: Madagascar customs and UN COMTRADE.
Low potential tax yield dummy	Dummy that takes value 1 if the hypothetical tax burden associated with valuing the declaration using external reference prices is equal to or lower than 20,000 USD. Defined at the declaration level. Source: Madagascar customs and UN COMTRADE.
G. Inspector characteristics	
Male	Dummy variable taking value 1 if the inspector is male and 0 otherwise. Defined at the inspector level. Source: Madagascar customs.
Age	Age of the inspector in years. Defined at the inspector level. Source: Madagascar customs.
Average tenure 1-2 years	Dummy variable that takes value 1 if the average (within-sample) tenure of the inspector in Toamasina port during the period in which she was active was between 1 and 2 years and 0 otherwise. Only the period before delegated randomization is considered when calculating the average tenure. Defined at the inspector level. Source: Madagascar customs.
Average tenure 2-3 years	Dummy that takes value 1 if the average (within-sample) tenure of the inspector in Toamasina port during the period in which we was active was between 2 and 3 years and 0 otherwise. Only the period before delegated randomization is considered when calculating the average tenure. Defined at the inspector level. Source: Madagascar customs.
Economics degree	Dummy variable that takes value 1 if the inspector has a degree in economics and 0 otherwise. Defined at the inspector level. Source: Madagascar customs.
Management degree	Dummy variable that takes value 1 if the inspector has a degree in management and 0 otherwise. Defined at the inspector level. Source: Madagascar customs.
Law degree	Dummy variable that takes value 1 if the inspector has a law degree and 0 otherwise. Defined at the inspector level. Source: Madagascar customs.

Table A1: Variable Definitions, 5/5

Variable name	**Variable definition and data source(s)**
H. Survey responses	
Overall job satisfaction	Inspector response to the question "Overall, how satisfied are you with your job", (1="Very dissatisfied", 2="Dissatisfied", 3="Neither satisfied nor dissatisfied", 4="Satisfied", 5="Very satisfied"). Defined at the inspector level. Source: authors' survey.
Pay satisfaction	Inspector response to the question "Overall, how satisfied are you with your current level of overall compensation (salary and bonuses)?" (1="Very dissatisfied", 2="Dissatisfied", 3="Neither satisfied nor dissatisfied", 4="Satisfied", 5="Very satisfied"). Defined at the inspector level. Source: authors' survey.
Esprit de corps	Inspector response to the question "How proud are you to work for Madagascar customs?" (1="Not proud at all", 2 "Somewhat proud", 3 "Proud", 4="Very proud", 5="Extremely proud"). Defined at the inspector level. Source: authors' survey.
Sufficient discretion	Inspector response to the question "I have sufficient discretion to decide to inspect, in the most appropriate way, the declarations which I am in charge of clearing (that is to say I have sufficient latitude to change the proposed inspection channel)" (1="Strongly disagree", 2="Disagree", 3="Neither agree nor disagree", 4="Agree", 5="Strongly agree"). Defined at the inspector level. Source: authors' survey.
Sufficient training	Inspector response to the question "To what extent do you agree with the statement "I am sufficiently well trained to do my job well" (1="Strongly disagree", 2="Disagree", 3="Neither agree nor disagree", 4="Agree", 5="Strongly agree"). Defined at the inspector level. Source: authors' survey.
Knowledge about risky firms	Inspector response to the question "To what extent do you agree with the statement "I know the firms most likely to cheat", (1="Strongly disagree", 2="Disagree", 3="Neither agree nor disagree", 4="Agree", 5="Strongly agree"). Defined at the inspector level. Source: authors' survey.
Corruption brokers	Inspector response to the question "To what extent do you agree with the statement "Brokers act with integrity", (1="Strongly disagree", 2="Disagree", 3="Neither agree nor disagree", 4="Agree", 5="Strongly agree"). Defined at the inspector level. Source: authors' survey.
Corruption colleagues	Inspector response to the question "To what extent do you agree with the statement "My colleagues act with integrity"?", (1="Strongly disagree", 2="Disagree", 3="Neither agree nor disagree", 4="Agree", 5="Strongly agree"). Defined at the inspector level. Source: authors' survey.
Corruption supervisor	Inspector response to the question "To what extent do you agree with the statement "My supervisor acts with integrity", (1="Strongly disagree", 2="Disagree", 3="Neither agree nor disagree", 4="Agree", 5="Strongly agree"). Defined at the inspector level. Source: authors' survey.
Unethical behaviour is sanctioned	Inspector response to the question "To what extent do you agree with the statement "Non-ethical behavior is sanctioned", (1="Strongly disagree", 2="Disagree", 3="Neither agree nor disagree", 4="Agree", 5="Strongly agree"). Defined at the inspector level. Source: authors' survey.
Promotions are fair	Inspector response to the question "To what extent do you agree with the statement "Promotions in customs are fair", (1="Strongly disagree", 2="Disagree", 3="Neither agree nor disagree", 4="Agree", 5="Strongly agree"). Defined at the inspector level. Source: authors' survey.

Table A2: Descriptive Statistics on Importer-Broker Relationships

	By importer		By importer-semester	
Number of brokers	N	%	N	%
1	2,319	63.36	8,077	83.41
2	765	20.90	1,200	12.39
3	322	8.80	284	2.93
4	139	3.80	92	0.95
5	57	1.56	20	0.21
6	29	0.79	8	0.08
7	11	0.30	1	0.01
8	8	0.22	1	0.01
9	5	0.14		
10	5	0.14		
Total	3,660	100.00	9,683	100.00

Notes: The table shows the distribution of the number of brokers each importer works with over the period. The sample covers the period January 1, 2015 to November 17, 3018.

Table A3: Descriptive Statistics - Before Delegated Randomization

Before delegated randomization of inspector assignment	Other declarations			Excess interaction declarations (corruption suspected)		
	Average	**Std. dev.**	**Obs.**	**Average**	**Std. dev.**	**Obs.**
Excess interaction						
Excess interaction share	0.00	0.02	40,397	0.11	0.06	4,661
Excess interaction share - inspector logits	0.00	0.02	40,397	0.11	0.06	4,661
Controls						
Risk characteristics						
Risk score	6.51	2.87	39,876	7.46	2.08	4,646
Tax rate	0.30	0.14	40,397	0.36	0.11	4,661
Red channel dummy	0.28	0.45	40,397	0.31	0.46	4,661
Mixed shipment dummy	0.34	0.47	40,397	0.48	0.50	4,661
Differentiated share	0.68	0.46	40,397	0.78	0.39	4,661
Valuation advice dummy	0.08	0.27	40,397	0.21	0.41	4,661
Additional characteristics						
Log initial weight	10.00	1.73	40,397	10.21	1.17	4,661
Log port authority weight	10.55	1.08	23,314	10.51	0.94	2,982
Log initial value	10.08	1.18	40,397	10.13	0.87	4,661
Log initial unit price (relative to internal prices)	-0.09	0.53	40,380	-0.16	0.52	4,653
Initial hypothetical tax revenue losses (internal prices)	0.08	0.50	40,380	0.16	0.51	4,653
High potential tax yield dummy	0.26	0.44	28,547	0.50	0.50	2,855
Customs outcomes						
Main outcomes						
Time	2.99	1.66	37,337	3.06	1.76	4,272
Fraud	0.08	0.27	40,397	0.13	0.34	4,661
Δ log value	0.02	0.08	40,322	0.03	0.09	4,648
Δ log tax	0.02	0.09	36,196	0.03	0.10	4,429
Hypothetical tax revenue losses (internal prices)	0.08	0.49	40,380	0.15	0.51	4,653
Additional outcomes						
Weight gap (port authority weight)	0.01	0.30	22,983	0.04	0.36	2,933
Hypothetical tax revenue losses (internal prices, port authority weight)	0.09	0.55	21,168	0.21	0.60	2,797
Hypothetical tax revenue losses (external reference prices)	0.57	0.95	28,547	1.11	1.09	2,855
Hypothetical tax revenue losses (external reference prices, port authority weight)	0.36	1.13	14,742	0.95	1.17	1,733
Hypothetical tax revenue losses (valuation advice)	0.10	0.18	3,280	0.23	0.26	978

Notes: excess interaction declarations are those that are handled by an inspector whose excess inspection share (the difference between the share of given broker's declarations handled by the inspector in question and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors was conditionally random as prescribed by official rules) for which we can reject the null hypothesis of conditional random assignment using simulation methods (as described in section 4). The sample covers the period Jan 1, 2015 to Nov 17, 2017, i.e. the period before delegated random assignment.

Table A4: Descriptive Statistics - During Delegated Randomization

During delegated randomization of inspector assignment						
	Randomized declarations			**Declarations withheld from randomization (corruption suspected)**		
	Average	**St. dev.**	**Obs.**	**Average**	**St. dev.**	**Obs.**
Excess interaction						
Excess interaction share	0.01	0.03	16,461	0.07	0.09	1,275
Excess interaction share - inspector logits	0.01	0.04	16,461	0.07	0.10	1,275
Controls						
Risk characteristics						
Risk score	6.14	2.97	15,925	7.31	2.11	1,242
Tax rate	0.29	0.14	16,461	0.38	0.09	1,275
Red channel dummy	0.17	0.38	16,461	0.04	0.20	1,275
Mixed shipment dummy	0.30	0.46	16,461	0.52	0.50	1,275
Differentiated share	0.68	0.46	16,461	0.77	0.39	1,275
Valuation advice dummy	0.08	0.27	16,461	0.17	0.38	1,275
Additional characteristics						
Log initial weight	9.99	1.79	16,461	10.15	1.00	1,275
Log port authority weight	10.66	1.92	6,723	10.06	1.61	515
Log initial value	10.17	1.23	16,461	10.01	0.88	1,275
Log initial unit price (relative to internal prices)	-0.05	0.47	16,454	-0.24	0.53	1,272
Initial hypothetical tax revenue losses (internal prices)	0.05	0.46	16,454	0.25	0.52	1,272
High potential tax yield dummy	0.23	0.42	12,023	0.62	0.49	730
Customs outcomes						
Main outcomes						
Log clearance time (hours)	3.65	1.30	16,432	2.79	1.68	563
Fraud record dummy	0.09	0.28	16,461	0.12	0.32	1,275
Δ log value	0.02	0.08	16,438	0.02	0.09	1,271
Δ log tax	0.02	0.10	14,386	0.03	0.10	1,254
Hypothetical tax revenue losses (internal prices)	0.04	0.45	16,454	0.24	0.52	1,272
Additional outcomes						
Hypothetical tax revenue losses (external reference prices)	0.49	0.91	12,023	1.40	1.04	730
Hypothetical tax revenue losses (valuation advice)	0.12	0.16	1,288	0.22	0.20	220

Notes: Randomized declarations are those for whom the assignment of the initial inspector was randomized by GasyNet. Declarations withheld from randomization were withheld from randomization by GasyNet by the customs IT department. The sample covers the period November 18, 2017 to November 17, 2018.

Table A5: Persistence of Corruption

		Correlation matrix						
		Excess interaction share	Lagged excess interaction share	Excess interaction indicator	Lagged excess interaction indicator	Withheld from randomization (WFR)	Lagged WFR	Random excess interaction share
Excess interaction share	ρ	1						
	N	5,124						
Lagged excess interaction share	ρ	0.343***	1					
	N	3,339	3,339					
Excess interaction indicator	ρ	0.554***	0.266***	1				
	N	5,117	3,337	5,117				
Lagged excess interaction indicator	ρ	0.286***	0.543***	0.340***	1			
	N	3,335	3,335	3,333	3,335			
Withheld from randomization (WFR)	ρ	0.327***	0.088**	0.461***	0.051	1		
	N	987	816	986	816	987		
Lagged WFR	ρ	0.287***	0.392***	0.319***	0.448***	0.342***	1	
	N	415	415	414	415	415	415	
Random excess interaction share	ρ	0.836***	0.136***	0.192***	0.173***	0.001	-0.006	1
	N	985	816	984	816	985	415	985

Notes: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. The unit of observation used for the calculation of the correlations is the average across declarations handled by an inspector-broker pair in a given semester. The sample covers the period January 1, 2015 to November 17, 2018.

Table A6: Within-Week Profile of Days Worked and Declarations Handled

	Inspectors				Brokers			
	Weekdays worked		**Declarations**		**Weekdays worked**		**Declarations**	
	Average	St. dev.	Average	St. dev.	Average	St. dev.	Average	St. dev.
Monday	82.4%	4.9%	21.4%	2.1%	40.6%	22.7%	22.4%	13.2%
Tuesday	86.0%	7.9%	21.5%	2.2%	38.5%	22.4%	20.2%	9.8%
Wednesday	85.5%	7.8%	20.9%	2.1%	37.9%	23.0%	20.0%	10.9%
Thursday	84.0%	9.0%	19.4%	1.7%	39.0%	22.7%	20.8%	13.8%
Friday	79.7%	10.8%	16.6%	2.1%	32.5%	22.0%	16.5%	11.8%

Notes: An inspector (a broker) is defined to work on a given weekday if she assesses (registers) at least one declaration on that weekday. For each inspector and broker we identify the weeks they work as those when they work at least one day. Focusing on the statistic of 82.4 percent in the first column, its interpretation is that inspectors on average work 82 percent of the Mondays of all weeks they work. Focusing on the statistic of 21.4 percent in the third column, it indicates that inspectors clear 21% of their declarations on Mondays (the percentages in this column add to 100).

Table A7: Determinants of Excess Interaction

Dependent variable:	**Excess interaction share**			
	(1)	(2)	(3)	(4)
Tax rate	0.025**	0.020**	0.020**	0.011**
	(0.011)	(0.008)	(0.007)	(0.005)
Risk score	0.001**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Mixed shipment dummy	-0.000	-0.000	-0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Differentiated share	0.002	-0.000	-0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Valuation advice dummy	0.014*	0.009**	0.009**	0.005**
	(0.007)	(0.004)	(0.003)	(0.002)
Red channel dummy	0.000	-0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Log initial value			0.000	-0.000
			(0.001)	(0.000)
Log initial unit price (rel. to internal prices)			-0.002	-0.001
			(0.001)	(0.001)
Month-year fixed effects	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes	Yes
Inspector fixed effects	No	Yes	Yes	Yes
Broker fixed effects	No	Yes	Yes	Yes
Importer fixed effects	No	No	No	Yes
Observations	44,522	44,522	44,497	43,669
R-squared	0.072	0.225	0.226	0.377

Notes: Standard errors clustered two-way by inspector and by broker are presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A8: Excess Interaction and Trade Elasticity Proxies

Before delegated randomization of inspector assignment			
Dependent variables	**Trade elasticity (Fontagne et al. 2022)**	**Trade elasticity (Broda and Weinstein 2006)**	**Relationship stickiness (Martin et al. 2020)**
	(1)	(2)	(3)
Excess interaction share	1.818	5.440	0.226
	(1.315)	(6.024)	(0.139)
Observations	44,578	43,794	43,157
R-squared	0.000	0.000	0.001

Notes: Standard errors clustered two-way by inspector and by broker are presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). Declaration characteristics include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A9: Tax Evasion Risk and Excess Interaction - Inspector-Specific Logit Models

	Before delegated randomization of inspector assignment					
Dependent variable:	**Risk score**	**Tax rate**	**Red channel dummy**	**Mixed shipment dummy**	**Differentiated share**	**Valuation advice dummy**
	(1)	(2)	(3)	(4)	(5)	(6)
Excess interaction share - Inspector logits	4.948***	0.297***	-0.016	0.763**	0.469**	0.870**
	(1.038)	(0.068)	(0.230)	(0.315)	(0.184)	(0.322)
Observations	44,522	45,058	45,058	45,058	45,058	45,058
R-squared	0.006	0.010	0.000	0.005	0.002	0.018
Dependent variable:		**Log initial value**	**Log initial weight**	**Log initial unit price**	**Initial hyp. tax rev. losses**	**High potential tax yield dummy**
		(7)	(8)	(9)	(10)	(11)
Excess interaction share - inspector logits		0.314	1.535***	-0.541**	0.571**	1.488***
		(0.346)	(0.479)	(0.237)	(0.240)	(0.254)
Observations		45,058	45,058	45,033	45,033	31,402
R-squared		0.000	0.002	0.002	0.003	0.020

Notes: Standard errors clustered two-way by inspector and by broker are presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share - inspector logits* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using inspector-specific binomial logit models (as explained in Section 4). "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A10: Differential Treatment - Inspector-specific Logit Models

Before delegated randomization of inspector assignment					
Dependent variable:	**Time**	**Fraud**	**Δ log value**	**Δ log tax**	**Hyp. tax revenue losses**
	(1)	(2)	(3)	(4)	(5)
Excess interaction share - inspector logits	-1.875***	-0.252***	-0.075***	-0.080***	0.327*
	(0.314)	(0.094)	(0.020)	(0.027)	(0.174)
Declaration characteristics	Yes	Yes	Yes	Yes	Yes
Inspector fixed effects	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.318	0.214	0.152	0.132	0.210

Notes: Standard errors clustered two-way by inspector and by broker are presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share - inspector logits* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using inspector-specific binomial logit models (as explained in Section 4). Declaration characteristics include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

B Propensity Score Matching Approach

Declarations subject to excess interaction are not randomly selected as is shown in Section 5. One may be concerned that our estimates of differential treatment of such declarations by inspectors (i.e., estimates of Equation (5)) may be impacted by selection bias. To address this potential bias, we implement a propensity score matching (PSM) approach, in which we consider being handled by an inspector who has significant excess interaction with the broker that registered the declaration as the "treatment". The PSM approach matches each treated declaration with the most "similar" control declarations (not subject to excess interaction), i.e., those with the closest propensity score, the latter being obtained from a regression of treatment status on a set of declaration characteristics. Specifically, we estimate the following model for the probability of being subject to significant excess interaction:

$$Prob(SEI_d) = (\beta_X X_d + \epsilon_d) \tag{6}$$

where SEI_d is a dummy that equals 1 if the declaration is entered by a broker in significant excess interaction with the inspector that assesses it, based on our calibrated excess interaction measures. The vector of declaration characteristics X_d includes the risk score, the tax rate, a dummy for the red channel, a dummy for being a mixed shipment, the share of differentiated products, a dummy for GasyNet's valuation advice, the inital weight (in logs), and the initial value (in logs). ϵ_d is an i.i.d error. We use probit estimation for Equation (6) and obtain an estimated propensity score ps_d for each declaration.

Following Rosenbaum and Rubin (1983) and Dehejia and Wahba (2002), we compute balancing tests to assess the extent to which matching corrects for differences in the distribution of characteristics between the treated and control declarations. The results from the tests are presented in Appendix Table A11. Treated and matched control declarations do not differ significantly in any of the characteristics.

We use the estimated propensity scores in two ways. First, we use a nearest neighbor matching algorithm to identify for each declaration with excess interaction which is the control declaration that is most similar according to the estimated propensity score, limiting observations to those in the region of common support. We estimate Equation (5) using this matched sample of declarations. The results are shown in panel A of Appendix Table A12. Second, we use the propensity scores as weights in propensity score weighted regressions as proposed by Hirano et al. (2003). We estimate Equation (5) using as weights 1 for declarations with significant excess interaction and $ps_d/(1 - ps_d)$ for declarations without excess interaction. The results are shown in panel B of Appendix Table A12. Overall the estimated coefficients are similar to the OLS estimates presented in Table 3.

Table A11: Balancing Tests from Propensity Score Matching

	Treated declarations		Control declarations		Difference	P-value
	Average	**Observations**	**Average**	**Observations**		**(two-sided test)**
Risk score	7.456	4,646	7.392	4,074	0.064	0.166
Tax rate	0.356	4,646	0.352	4,074	0.004	0.090
Red channel dummy	0.313	4,646	0.321	4,074	-0.008	0.405
Mixed shipment dummy	0.478	4,646	0.491	4,074	-0.013	0.228
Differentiated share	0.782	4,646	0.773	4,074	0.008	0.333
Valuation advice dummy	0.212	4,646	0.195	4,074	0.017	0.047
Log initial weight	10.211	4,646	10.181	4,074	0.030	0.268
Log initial value	10.133	4,646	10.115	4,074	0.019	0.341

Notes: Treated declarations are ones subject to significant excess interaction between inspectors and brokers, with excess interaction calculated using calibration methods (as explained in section 4). Control declarations are selected using nearest neighbor propensity score matching based on the risk score, the tax rate, a dummy for the red channel, a dummy for being a mixed shipment, the share of differentiated products, a dummy for GasyNet's valuation advice, the initial weight (in logs), and the initial value (in logs). The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A12: Differential Treatment - Matching Estimates

Before delegated randomization of inspector assignment					
Dependent variable	**Time**	**Fraud**	**Δlog value**	**Δlog tax**	**Hyp. tax revenue losses**
A. Matched sample					
	(1)	(2)	(3)	(4)	(5)
Excess interaction share	-2.178***	-0.260*	-0.080*	-0.075	0.280**
	(0.609)	(0.138)	(0.044)	(0.056)	(0.119)
Declaration characteristics	Yes	Yes	Yes	Yes	Yes
Inspector fixed effects	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	8,049	8,720	8,703	8,317	8,710
R-squared	0.387	0.268	0.204	0.184	0.333
B. Propensity score weighted least squares estimation					
	(6)	(7)	(8)	(9)	(10)
Excess interaction share	-2.009***	-0.209***	-0.069***	-0.081***	0.388***
	(0.181)	(0.036)	(0.012)	(0.014)	(0.058)
Declaration characteristics	Yes	Yes	Yes	Yes	Yes
Inspector fixed effects	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	41,094	44,492	44,404	40,467	44,467
R-squared	0.319	0.183	0.134	0.117	0.208

Notes: Standard errors clustered two-way by inspector and by broker are presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). Declaration characteristics include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice. "Observations" refers to the number of non-singleton observations. Panel A restricts the sample to matched declarations selected using nearest neighbor propensity score matching on the basis of the risk score, the tax rate, a dummy for the red channel, a dummy for being a mixed shipment, the share of differentiated products, a dummy for GasyNet's valuation advice, the inital weight (in logs), and the initial value (in logs). Panel B presents propensity score weighted regressions as proposed by Hirano et al. (2003). OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A13: Differential Treatment - Alternative Controls

Before delegated randomization of inspector assignment					
Dependent variable:	**Time**	**Fraud**	**Δ log value**	**Δ log tax**	**Hyp. tax revenue losses**
A. Including Only Month-Year Fixed Effects					
	(1)	(2)	(3)	(4)	(5)
Excess interaction share	-1.481**	-0.160	-0.053*	-0.060*	0.531**
	(0.586)	(0.101)	(0.028)	(0.030)	(0.253)
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.263	0.174	0.116	0.099	0.028
B. Including Month-Year and Inspector Fixed Effects					
	(6)	(7)	(8)	(9)	(10)
Excess interaction share	-1.519***	-0.123	-0.041*	-0.047*	0.504*
	(0.519)	(0.085)	(0.022)	(0.025)	(0.246)
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.287	0.178	0.121	0.103	0.030
C. Including Month-Year, Inspector, and Broker Fixed Effects					
	(11)	(12)	(13)	(14)	(15)
Excess interaction share	-1.810***	-0.221**	-0.072***	-0.079**	0.282
	(0.342)	(0.101)	(0.022)	(0.029)	(0.176)
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.303	0.195	0.139	0.119	0.073
D. Including Month-Year, Inspector, Broker, and Source Country Fixed Effects					
	(16)	(17)	(18)	(19)	(20)
Excess interaction share	-1.937***	-0.236**	-0.072***	-0.079**	0.400**
	(0.358)	(0.103)	(0.022)	(0.030)	(0.176)
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.309	0.198	0.141	0.121	0.146
E. Adding All Covariates in Table 2 as Controls (With Month-Year, Inspector, Broker, Source Country, and HS2 Fixed Effects)					
	(21)	(22)	(23)	(24)	(25)
Excess interaction share	-1.806***	-0.174*	-0.057**	-0.062	0.087***
	(0.330)	(0.102)	(0.024)	(0.038)	(0.025)
Observations	28,772	31,102	31,049	27,825	31,102
R-squared	0.323	0.213	0.167	0.143	0.964

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). All specifications include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice. The specifications also include in Panel A month-year fixed effects, in Panel B inspector and month-year fixed effects, in Panel C inspector, broker, and month-year fixed effects, in panel D inspector, broker, month-year, and source-country fixed effects, and in Panel E all covariates used in Table 2 and inspector, broker, source-country, HS2 product, and month-year fixed effects. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A14: Differential Treatment - Alternative Standard Errors, Collapsed Data, Excluding Brokers with the Most Excess Interaction

Before delegated randomization of inspector assignment					
Dependent variable:	**Time**	**Fraud**	**Δ log value**	**Δ log tax**	**Hyp. tax revenue losses**
A. Different Types of Clusters for Standard Errors					
	(1)	(2)	(3)	(4)	(5)
Excess interaction share	-2.008	-0.275	-0.079	-0.086	0.389
Robust SE	(0.182)***	(0.036)***	(0.011)***	(0.013)***	(0.058)***
SE clustered by inspector	(0.289)***	(0.056)***	(0.017)***	(0.025)***	(0.103)***
SE clustered by broker	(0.287)***	(0.101)***	(0.020)***	(0.025)***	(0.168)**
SE clustered by broker and inspector (baseline)	(0.361)***	(0.101)***	(0.022)***	(0.031)***	(0.175)**
SE three-way clustered by inspector, broker, and semester	(0.558)**	(0.100)**	(0.026)**	(0.032)**	(0.174)*
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.318	0.214	0.152	0.132	0.211
B. Data Collapsed at the Broker-Inspector-Semester Level					
	(6)	(7)	(8)	(9)	(10)
Excess interaction share	-1.565***	-0.238*	-0.047	-0.038	0.053
	(0.485)	(0.118)	(0.033)	(0.039)	(0.154)
Observations	4,106	4,123	4,122	4,015	4,123
R-squared	0.512	0.330	0.248	0.206	0.273
C. Dropping Top 5 Brokers with the Largest Share of Declarations with Excess Interaction Each Semester					
	(11)	(12)	(13)	(14)	(15)
Excess interaction share	-2.352***	-0.188**	-0.072**	-0.088**	0.193
	(0.365)	(0.090)	(0.029)	(0.032)	(0.131)
Observations	37,046	40,035	39,956	36,340	40,014
R-squared	0.310	0.221	0.156	0.137	0.197

Notes: Standard errors (SE) are presented in parentheses. In Panel A we list how such standard errors are constructed in the leftmost column. In Panel B and C standard are clustered two-ways by inspector and brokers. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). All specifications include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice, inspector, broker, source country, HS2-product, and month-year fixed effects. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A15: Differential Treatment - Additional Fixed Effects

Before delegated randomization of inspector assignment					
Dependent variable:	**Time**	**Fraud**	**Δ log value**	**Δ log tax**	**Hyp. tax revenue losses**
A. Controlling for Inspector-Semester and Broker-Semester Fixed Effects					
	(1)	(2)	(3)	(4)	(5)
Excess interaction share	-1.841***	-0.232**	-0.067***	-0.081***	0.310*
	(0.354)	(0.093)	(0.018)	(0.022)	(0.153)
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.340	0.235	0.173	0.153	0.223
B. Controlling for Inspector-Semester, Broker-Semester, and Importer-Semester Fixed Effects					
	(6)	(7)	(8)	(9)	(10)
Excess interaction share	-1.855***	-0.104*	-0.045**	-0.053**	0.223***
	(0.372)	(0.060)	(0.020)	(0.022)	(0.080)
Observations	38,624	41,972	41,885	38,045	41,952
R-squared	0.461	0.412	0.383	0.381	0.477
C. Controlling for Inspector-Month and Broker-Month Fixed Effects					
	(11)	(12)	(13)	(14)	(15)
Excess interaction share	-1.810***	-0.184**	-0.057***	-0.068***	0.255
	(0.317)	(0.087)	(0.018)	(0.023)	(0.151)
Observations	41,098	44,510	44,422	40,449	44,485
R-squared	0.386	0.281	0.219	0.208	0.258
D. Controlling for Importer-Broker Fixed Effects					
	(16)	(17)	(18)	(19)	(20)
Excess interaction share	-1.995***	-0.132*	-0.054**	-0.061**	0.236***
	(0.316)	(0.076)	(0.022)	(0.026)	(0.084)
Observations	39,422	42,761	42,674	38,803	42,738
R-squared	0.411	0.349	0.326	0.327	0.447

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). All specifications include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, a dummy indicating the declaration was subject to valuation advice, and source country and HS2-product fixed effects. Specifications in panels A, B, and D also include month-year fixed effects. Specifications in panel D also include inspector fixed effects. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A16: Differential Treatment - Alternative Measures of Excess Interaction and Samples

Before delegated randomization of inspector assignment					
Dependent variable:	**Time**	**Fraud**	**Δ log value**	**Δ log tax**	**Hyp. tax revenue losses**
A. Indicator for Significant excess Interaction (99 Percent Confidence)					
	(1)	(2)	(3)	(4)	(5)
Excess interaction indicator	-0.204***	-0.026*	-0.008**	-0.009**	0.025
	(0.058)	(0.014)	(0.003)	(0.004)	(0.020)
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.317	0.213	0.152	0.132	0.210
B. Indicator for Significant Excess Interaction (95 Percent Confidence)					
	(6)	(7)	(8)	(9)	(10)
Excess interaction indicator	-0.199***	-0.026*	-0.008**	-0.008**	0.025
	(0.058)	(0.013)	(0.003)	(0.004)	(0.020)
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.317	0.213	0.152	0.132	0.210
C. Indicator for Significant Excess Interaction (99.9 Percent Confidence)					
	(11)	(12)	(13)	(14)	(15)
Excess interaction indicator	-0.199***	-0.026*	-0.008**	-0.009*	0.025
	(0.059)	(0.015)	(0.003)	(0.004)	(0.020)
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.317	0.213	0.152	0.132	0.210
D. Alternative Sample Including Brokers with More than 20 Declarations per Semester					
	(16)	(17)	(18)	(19)	(20)
Excess interaction share	-2.005***	-0.276**	-0.079***	-0.085***	0.413**
	(0.359)	(0.100)	(0.023)	(0.030)	(0.172)
Observations	41,245	44,655	44,565	40,591	44,630
R-squared	0.318	0.213	0.152	0.131	0.210
E. Alternative Sample Including Brokers with More than 100 Declarations per Semester					
	(21)	(22)	(23)	(24)	(25)
Excess interaction share	-2.128***	-0.330***	-0.092***	-0.105***	0.356**
	(0.400)	(0.104)	(0.021)	(0.026)	(0.150)
Observations	36,485	39,462	39,385	36,039	39,438
R-squared	0.319	0.212	0.150	0.130	0.219
F. Alternative Sample Including All Brokers					
	(26)	(27)	(28)	(29)	(30)
Excess interaction share	-2.006***	-0.275**	-0.079***	-0.085***	0.418**
	(0.359)	(0.100)	(0.023)	(0.030)	(0.172)
Observations	41,262	44,672	44,582	40,606	44,647
R-squared	0.318	0.213	0.152	0.131	0.209

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). All specifications include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, a dummy indicating the declaration was subject to valuation advice, and inspector, broker, source country, HS2-product, and month-year fixed effects. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A17: Do Importers Strategically Select Brokers?

Before delegated randomization of inspector assignment					
Dependent variable	**Risk score**	**Tax rate**	**Valuation advice dummy**	**Log initial unit price**	**Initial hyp. tax rev. losses**
	(1)	(2)	(3)	(4)	(5)
Brokers' excess interaction (that semester)	0.214	0.059***	0.118**	-0.150*	0.171*
	(0.174)	(0.019)	(0.049)	(0.088)	(0.086)
Importer-semester fixed effects	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	41,972	42,415	42,415	42,395	42,395
R-squared	0.793	0.709	0.382	0.437	0.439

Notes: Standard errors clustered two-way by broker and by importer presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Brokers' excess interaction (that semester)* is the share of declarations registered by the broker in a semester that are characterized by significant excess interaction as calculated by calibration methods (see Section 4 for details). The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A18: Item-level Regressions

	Before delegated randomization of inspector assignment				
Dependent variable	**Log initial unit price**	**Δlog unit price**	**Log final unit price**	**Δlog weight**	**Hyp. tax revenue losses**
	(1)	(2)	(3)	(4)	(5)
Excess interaction share	-0.408*	-0.078***	-0.484***	-0.006	0.294
	(0.237)	(0.023)	(0.226)	(0.004)	(0.190)
Inspector-HS 8-digit product fixed effects	Yes	Yes	Yes	Yes	Yes
Declaration characteristics	Yes	Yes	Yes	Yes	Yes
Item characteristics	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	134,013	133,775	134,013	134,000	134,013
R-squared	0.624	0.200	0.620	0.148	0.359

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). Item characteristics include the tax rate. Declaration characteristics include the risk score, a dummy for the red channel, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A19: Heterogeneity in Differential Treatment

Before delegated randomization of inspector assignment					
Dependent variable:	**Time**	**Fraud**	**Δ log value**	**Δ log tax**	**Hyp. tax revenue losses**
	(1)	(2)	(3)	(4)	(5)
Excess interaction share	-1.974**	0.023	-0.011	-0.100	-0.199
	(0.922)	(0.079)	(0.036)	(0.065)	(0.208)
Tax rate	0.913***	0.186***	0.048***	0.040**	0.095
	(0.211)	(0.043)	(0.010)	(0.019)	(0.081)
Excess interaction share*Tax rate	-0.100	-0.862**	-0.196	0.040	1.698**
	(2.644)	(0.342)	(0.121)	(0.209)	(0.675)
Declaration characteristics	Yes	Yes	Yes	Yes	Yes
Inspector fixed effects	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.318	0.214	0.152	0.132	0.211

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). Declarations characteristics include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A20: Prevalence of Re-Assignments

	% of all declarations	**% of all re-assignments**	**probability of re-assignment conditional on initial state**
Declarations without initial excess interaction	**90.1%**		
Not re-assigned	84.1%		
Re-assigned to inspector without excess interaction (RNN)	5.7%	89.0%	6.3%
Re-assigned to inspector with excess interaction (RNE)	0.4%	5.9%	0.4%
Declarations with initial excess interaction	**9.9%**		
Not re-assigned	9.6%		
Re-assigned to inspector without excess interaction (REN)	0.3%	4.3%	2.8%
Re-assigned to inspector with excess interaction (REE)	0.0%	0.8%	0.5%
Any re-assignment	6.4%		

Notes: Re-assignment No Excess -> No Excess (RNN) are cases in which a declaration is taken from an inspector who did not act significantly excessively frequently with the broker handling the declaration to another inspector who did not interact significantly excessively frequently with the broker either. Re-assignment Excess -> No Excess (REN) are cases in which a declaration is taken away from an inspector who interacts significantly excessively frequently with the broker in question to one who was not. RNE and REE are defined analogously. Measures of excess interaction are calculated using calibration methods (see section 4 for details). The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A21: Impact of Re-Assignments on Customs Outcomes

	Before delegated randomization of inspector assignment				
Dependent variable:	**Time**	**Fraud**	**Δ log value**	**Δ log tax**	**Hyp. tax revenue losses**
	(1)	(2)	(3)	(4)	(5)
Excess interaction share	-1.989***	-0.260**	-0.074***	-0.079**	0.387**
	(0.351)	(0.103)	(0.023)	(0.032)	(0.179)
Re-assignment No Excess -> No Excess (RNN)	-0.390***	0.040***	0.010***	0.014***	0.003
	(0.106)	(0.010)	(0.002)	(0.003)	(0.015)
Re-assignment No Excess -> Excess (RNE)	-0.908**	-0.005	0.001	-0.001	-0.016
	(0.405)	(0.034)	(0.012)	(0.014)	(0.066)
Re-assignment Excess->No Excess (REN)	-0.238	0.099**	0.048***	0.043**	-0.071
	(0.205)	(0.043)	(0.016)	(0.016)	(0.061)
Re-assignment Excess -> Excess (REE)	0.092	0.197**	0.055**	0.062**	0.043
	(0.272)	(0.076)	(0.025)	(0.024)	(0.117)
Declaration characteristics	Yes	Yes	Yes	Yes	Yes
Inspector fixed effects	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes
P-values					
test for difference (RNN)=(RNE)	0.170	0.187	0.413	0.249	0.760
test for difference (REN)=(RNN)	0.496	0.182	0.025	0.092	0.275
test for difference (RNE)=(REE)	0.049	0.016	0.071	0.035	0.581
Observations	41,121	44,522	44,434	40,471	44,497
R-squared	0.322	0.215	0.154	0.134	0.211

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. The table considers re-assignments across inspectors made by the customs port manager. Re-assignments No Excess→ No Excess (RNN) are cases in which a declaration is taken from an inspector who did not act excessively frequently with the broker handling the declaration and is assigned to another inspector who did not interact excessively frequently with the broker either. Re-assignments Excess → No Excess (REN) are cases in which a declaration is taken away from an inspector who was interacting excessively frequently with the broker in question and is assigned to an inspector who was not. Re-assignments RNE, and REE are defined analogously. "Observations" refers to the number of non-singleton observations. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

C Calculation of counterfactual tax revenue in the absence of corruption

To assess how much tax revenue is lost because of the corruption scheme we detect, we conduct a back-of-the-envelope calculation of how much higher tax revenues would have been in the absence of excess interaction between inspectors and brokers. As an input into these calculations, we first estimate the impact of excess interaction between inspectors and brokers on each of the measures of hypothetical tax revenue losses described in Section 6, β_E in Equation (5). We then use these estimates to quantify the costs of corruption.

To obtain estimates of β_E, we estimate two variants of Equation (5). First, to set the scene Appendix Table A22 (panel A) estimates Equation (5) with all controls. This may result in a downward-biased estimate of β_E because some controls may be potentially endogenous to corruption: inspector and broker fixed effects and the risk score. Second, Appendix Table A22 (panel B) estimates a variant of Equation (5) that includes only controls that are plausibly exogenous to corruption: the tax rate, the dummy for mixed shipment, the share of differentiated products, source country fixed effects, HS 2-digit product fixed effects, and month-year fixed effects.

Column (1) in panel A shows that excess interaction is associated with underreporting of quantities, captured by the weight gap (final weight retained by customs relative to the weight measured by the port authority upon arrival) for the declaration. A 10 percent increase in the excess interaction share is associated with underreporting of quantities by 1.6 percent. Measures of tax revenue losses that consider undervaluation but do not capture this margin of evasion yield downward-biased estimates of the costs of corruption. By implication, the impact of corruption on our baseline measure of tax revenue losses in column (2) is overly conservative. Indeed, when we use a measure of tax revenue losses that corrects for underreporting of quantities as well as prices in column (3) we find a stronger impact of the excess interaction share. Another reason why our baseline impact may be downward-biased is that the price correction it embeds is based on median import unit prices which may themselves be underreported. To circumvent this problem, columns (4) and (5) show the impact of the excess interaction share on the measure of tax revenue losses based on prices reported by countries exporting to Madagascar, which are arguably less likely to be endogenous to underinvoicing in Madagascar, with column (5) also correcting for underreporting of quantities. Using external reference prices leads to a near doubling of the coefficient on the excess interaction share and an increase in the explanatory power of the model, as is evidenced by the higher R^2s. Column (6) presents estimates that use as the dependent variable the measure of tax revenue losses based on transaction-specific valuation advice provided by the third-party GasyNet, which are issued for a small subset of declarations.

We now turn to estimates of Equation (5) that exclude controls that could be endogenous to corruption. These are the estimates we will use to quantify the costs of corruption. Column (7) in panel B shows that the excess interaction share is no longer significantly correlated with the weight gap. Yet, correcting for underreporting of quantities has consistently higher impacts on tax revenue losses than in panel A. According to our preferred estimates of tax revenue losses which rely on the measure of hypothetical tax revenue losses based on exporter prices and corrected for potential underreporting of quantities in column (11), a 10 percent increase in the excess interaction share is associated with a 21 percent increase in tax revenue losses. For all measures of tax revenue losses excluding controls potentially endogenous to corruption, the estimates of the association between excess interaction and tax revenue losses are much higher; in most cases estimates roughly double in magnitude.

Next, we describe how we use these estimates of β_E to quantify the costs of corruption in terms of tax revenues lost. We calculate how much more tax revenue would have been collected if there was no *significant* excess interaction between inspectors and brokers. During the delegated randomization period we calculate how much more revenue would have been collected if there was no *significant* excess interaction and no withholding of declarations from the delegated randomization. We calculate separate counterfactual estimates for the period before and during the delegated randomization intervention for two reasons. First, the delegated randomization intervention may have had a deterrence effect. Second, the novel IT manipulation uncovered during the delegated randomization period arguably facilitates identification of the specific declarations that were the object of corruption schemes, i.e., those that were both withheld from delegated randomization and handled by inspectors that were interacting excessively frequently with the broker that registered the declarations.

Our measure of hypothetical tax revenue losses, denoted *loss*, is defined to be the difference between log hypothetical tax yield (based on a reference price) and log actual tax yield: $loss = log(T^H) - log(T)$. Analogously, we can define hypothetical tax revenue losses *in the absence of the corruption scheme* as the difference between hypothetical tax yield (based on a reference price) and tax yield *in the absence of the corruption scheme* (which is the unknown variable we are interested in measuring): $loss^{NC} = log(T^H) - log(T^{NC})$. These two definitions in turn imply that we can write the log tax yield in the absence of the corruption scheme as:

$$log(T^{NC}) = log(T) - (loss^{NC} - loss) \tag{7}$$

Focusing on the period before the delegated randomization intervention, we use the estimates of β_E presented in Panel B of Appendix Table A22 to obtain predicted hypothetical tax revenue losses *in the presence of* *the corruption scheme* as:

$$\widehat{loss} = \widehat{\beta_E} \times ES + \widehat{\beta_Z} Z \tag{8}$$

where the vector Z includes all explanatory variables other than ES. We can use the same estimates to predict counterfactual tax revenue losses that would have materialized *in the absence* of the corruption scheme as:[56]

$$\widehat{loss^{NC}} = \widehat{\beta_Z} Z \tag{9}$$

Subtracting Equation (8) from Equation (9) we have $\widehat{loss^{NC}} - \widehat{loss} = -\widehat{\beta_E} \times ES$ and we can now compute counterfactual tax yield in the absence of excess interaction by plugging $\widehat{\beta_E} ES$ into Equation (7) and taking exponents:

$$\widehat{T^{NC}} = T \times exp(\widehat{\beta_E} \times ES) \tag{10}$$

We construct measures of counterfactual tax yield *in the absence of the corruption scheme* ($\widehat{T^{NC}}$) for each declaration using alternative estimates of β_E for different measures of tax revenue losses. Comparing these measures of counterfactual tax yield *in the absence of the corruption scheme* ($\widehat{T}^{NC}$) to the actual tax yield provides an estimate of how much tax revenue would have been collected if significant excess interaction between inspectors and brokers was eliminated.

We calculate the *additional* revenue yield in the absence of significant excess interaction for each declaration and show the averages across declarations with significant excess interaction in the first two columns of Appendix Table A24 and the averages across all declarations in the last two columns of Appendix Table A24. Declarations with significant excess interaction yield more tax revenue, 11,423 USD on average, despite being undervalued, than the average declaration, which yields 10,446 USD. This finding reflects the fact that declarations with significant excess interaction are subject to higher tax rates, as was shown in Section 5. In the absence of the corruption scheme the average declaration with significant excess interaction would have yielded an additional 940 USD in tax revenue if we valued imports at the median import unit price and an additional 1,468 USD when also correcting for underreporting of quantities. According to our preferred counterfactual estimates, which evaluate hypothetical tax yield using prices reported by exporters and also correct for potential underreporting of quantities, tax yield per declaration would have been 2,962 USD higher. Put differently, the tax yield on declarations likely to be the object of corruption agreements would have been 26 percent points higher. This number is a lower bound on total tax revenue losses per

[56] Note that we are simply recalculating predicted tax revenue losses while assuming excess interaction ES is 0 for each declaration with significant excess interaction.

declaration associated with the corruption scheme since the set of declarations characterized by significant excess interaction likely also includes some that were randomly assigned and not the object of the scheme we uncover (as discussed in Section 4 our estimates of excess interaction have the potential for including false positives). Aggregate revenue yield would have been 3 percent higher.

Focusing on the delegated randomization period, we use the estimates of β_E, β_P, and β_{EP} presented in Appendix Table A23 and we follow the same logic as for the pre-period to obtain the counterfactual tax yield *in the absence of the corruption scheme* analogously to what is done in Equation (8) as:

$$\widehat{T^{NC}} = T \times exp(\widehat{\beta_E} \times ES + \widehat{\beta_P} \times PM + \widehat{\beta_{EP}} \times ES \times PM) \tag{11}$$

We construct measures of counterfactual tax yield *in the absence of* manipulation ($\widehat{T^{NC}}$) for each declaration using alternative estimates of β_E, β_P, and β_{EP} for different measures of tax revenue losses. To calculate how much additional tax would have been collected in the absence of corruption we subtract from these the actual tax yield.

We show estimates of the average additional tax yield per declaration for declarations with significant excess interaction that were withheld from randomization in the first two columns of Appendix Table A24 and the averages across all declarations in the last two columns of Appendix Table A24. Declarations with significant excess interaction withheld from randomization yield less tax revenue (8,645 USD) than the average declaration (10,749 USD). According to our preferred counterfactual estimates which calculate hypothetical tax yield using prices reported by exporters, declarations that were likely the object of corruption would have yielded an additional 11,223 USD in tax revenue, which represents a 129.8 percent increase over actual tax yield. More conservative estimates that calculate revenue losses using median import unit prices still predict a 43.3 percent gain in tax yield. Both estimates are conservative since we are not able to correct for potential underreporting of quantities for that period (due to lack of reliable data). According to our preferred estimates, aggregate tax yield in the delegated randomization period would have been 2.6 percent higher had the delegated randomization not been undermined by a new form of IT manipulation. While these back-of-the-envelope estimates are crude and must be interpreted with caution given the difficulties inherent in measuring hypothetical tax yield, they underscore that the corruption scheme we unveil substantially compromised fiscal performance in Madagascar.

Table A22: Excess Interaction and Tax Revenue Losses I

Before delegated randomization of inspector assignment						
Dependent variable:	**Weight gap**	**Hyp. tax revenue losses**				
reference price		Importer		Exporter		Third-party
weight correction		No	Yes	No	Yes	
A. Differential Treatment by Inspectors						
	(1)	(2)	(3)	(4)	(5)	(6)
Excess interaction share	0.155*	0.389**	0.575***	0.760***	1.126***	0.294**
	(0.079)	(0.175)	(0.145)	(0.251)	(0.277)	(0.114)
Declaration characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Inspector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Broker fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,750	44,497	23,937	31,103	16,457	4,254
R-squared	0.100	0.211	0.250	0.571	0.454	0.431
B. Overall Revenue Losses Associated with Corruption						
	(7)	(8)	(9)	(10)	(11)	(12)
Excess interaction share	0.088	0.732**	1.112***	1.659***	2.085***	0.851***
	(0.071)	(0.266)	(0.261)	(0.366)	(0.353)	(0.184)
Exogenous declaration characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,916	45,033	23,965	31,402	16,475	4,258
R-squared	0.095	0.181	0.222	0.532	0.420	0.342

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by official rules, calculated using calibration methods (as explained in Section 4). Declaration characteristics include the tax rate, the risk score, a dummy for the red channel, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating the declaration was subject to valuation advice. Exogenous declarations characteristics include the tax rate, the share of value accounted for by differentiated products, and a dummy indicating whether the declaration was mixed. "Importer", "Exporter" and "Third-party" refer, respectively, to median import unit prices, unit prices reported by countries exporting to Madagascar, and transaction-specific valuation advice provided by the third-party GasyNet based on its own proprietary data. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A23: Excess Interaction and Tax Revenue Losses II

During delegated randomization of inspector assignment			
Dependent variable:	**Hypothetical revenue loss**		
reference price	Importer	Exporter	Third-party
	(1)	(2)	(3)
Excess interaction share	0.146***	0.267***	0.024*
	(0.028)	(0.068)	(0.011)
Withheld from randomization (WFR)	0.043	0.021	0.184
	(0.160)	(0.269)	(0.162)
WFR*Excess interaction share	1.279***	3.328***	0.479**
	(0.327)	(0.638)	(0.206)
Exogenous declaration characteristics	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes
HS2-product fixed effects	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes
Observations	17,726	12,753	1,508
R-squared	0.149	0.544	0.436

Notes: Standard errors clustered two-way by inspector and by broker presented in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Excess interaction share* is the difference between the share of given broker's declarations handled by an inspector in a given semester and the hypothetical share she would be expected to handle if the allocation of declarations to inspectors were random conditional on their productivity, as prescribed by the official assignment rules, calculated using calibration (as explained in Section 4). Declaration characteristics include the tax rate, the share of value accounted for by differentiated products, a dummy indicating whether the declaration was mixed, and a dummy indicating whether valuation advice was issued. Exogenous declarations characteristics include the tax rate, the share of value accounted for by differentiated products, and a dummy indicating whether the declaration was mixed. "Importer", "Exporter" and "Third-party" refer, respectively, to median unit import prices, prices reported by countries exporting to Madagascar, and transaction-specific valuation advice provided by the third-party GasyNet based on its own proprietary data. "Observations" refers to the number of non-singleton observations. OLS estimation is used. The sample covers the period November 18, 2017 to November 17, 2018.

Table A24: Cost of Corruption

	Tax yield per declaration (average)	% Counterfactual increase without corruption	Tax yield per declaration (average)	% Counterfactual increase without corruption
A. Before Delegated Randomization of Inspector Assignment				
	Declarations with significant excess interaction		All declarations	
Actual tax yield	$11,423		$10,446	
Counterfactual tax yield without corruption, based on:				
internal reference price	$940	8.2%	$97	0.9%
internal reference price & measured weight	$1,468	12.8%	$152	1.5%
external reference price	$2,281	20.0%	$236	2.3%
external reference price & measured weight	$2,962	25.9%	$306	2.9%
third party valuation advice	$1,102	9.6%	$114	1.1%
B. During Delegated Randomization of Inspector Assignment				
	Declarations with significant excess interaction that were withheld from randomization		All declarations	
Actual tax revenue	$8,645		$10,749	
Additional counterfactual tax yield without corruption, based on:				
internal reference price	$3,745	43.3%	$95	0.9%
external reference price	$11,223	129.8%	$281	2.6%
third party valuation advice	$1,198	13.9%	$34	0.3%

Notes: Tax losses are calculated as the difference between the counterfactual tax yield collected in the absence of significant excess interaction and the actual tax yield. The counterfactual additional tax yield is calculated using measures of tax revenue losses based on different sets of reference prices (see Sections 3 and 7 for details).

Table A25: Characteristics of Inspectors and Brokers Participating in the Corruption Scheme

Dependent variable:	**Average excess interaction share**		
Panel A. Inspectors			
	(1)	(2)	(3)
Male	0.049*	0.048	0.010
	(0.029)	(0.029)	(0.044)
Average tenure: 1-2 years	0.075***	0.076***	0.149***
	(0.025)	(0.027)	(0.046)
Average tenure: 2-3 years	0.085**	0.080**	0.172***
	(0.034)	(0.037)	(0.044)
Age		-0.002	0.002
		(0.002)	(0.003)
Management degree			0.129**
			(0.048)
Economics degree			0.041
			(0.038)
Law degree			0.018
			(0.044)
Observations	29	29	18
R-squared	0.201	0.222	0.624
Panel B: Brokers			
	(4)	(5)	(6)
Based in Toamasina	0.059*	0.052	0.052
	(0.035)	(0.037)	(0.037)
Importer acting as own broker		-0.050	-0.045
		(0.033)	(0.036)
Average market share			-0.091
			(0.657)
Broker tenure: 5-10 years			0.044
			(0.048)
Broker tenure: more than 10 years			0.046
			(0.050)
Observations	63	63	63
R-squared	0.044	0.051	0.062

Notes: Standard errors in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. The average excess interaction share is measured as the share of declarations subject to significant excess interaction calculated using calibration methods (as explained in Section 4). The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).

Table A26: Inspectors' Survey Responses and Excess Interaction

Dependent variable:	**Overall job satisfaction**	**Pay satisfaction**	**Esprit de corps**	**Sufficient discretion**	**Sufficient training**	**Knowledge about risky firms**
	(1)	(2)	(3)	(4)	(5)	(6)
Average significant excess interaction	4.543**	-0.659	5.111*	-1.968	0.208	4.605**
	(1.839)	(2.515)	(2.744)	(2.441)	(0.288)	(1.774)
Observations	20	20	20	20	29	20
R-squared	0.253	0.004	0.162	0.035	0.019	0.272
	Corruption brokers	**Corruption colleagues**	**Corruption supervisors**	**Ethical behavior is sanctioned**	**Receives threats**	**Promotions are fair**
	(7)	(8)	(9)	(10)	(11)	(12)
Average significant excess interaction	2.239	0.364	4.033	-0.053	3.267	1.606
	(2.068)	(2.078)	(2.506)	(2.221)	(2.567)	(2.124)
Observations	20	20	20	20	20	20
R-squared	0.061	0.002	0.126	0.000	0.083	0.031

Notes: Standard errors in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *Average significant excess interaction* is measured as the share of declarations handled by the inspector that were subject to significant excess interaction calculated using calibration methods (as explained in Section 4). The dependent variables are taken from a nationwide survey of inspectors conducted in 2017, typically scored from 1 to 5 (see Table A1 part H for a detailed description of the variables).The sample covers the period January 1, 2015 to November 17, 2017 (i.e., before the delegated randomization intervention).