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Corruption Dynamics in International Trade

Evidence on Bribery and Tax Evasion from Tunisian Customs Transactions*

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Abstract

Every year low- and middle-income countries import goods worth more than $7 trillion, and in many states these shipments must first pass through the hands of corrupt customs officials. With such high stakes, policymakers require a deep understanding of both the causes and the effects of customs fraud. In addition, researchers have the opportunity to use trade corruption as a laboratory to discover new insights about corruption as a whole. One previously unexplored complexity is that bribe payers and bribe receivers often have repeated interactions; given corruption's characteristic contracting frictions, counterparty risks, and information asymmetries, these long-running relationships likely matter for a wide variety of outcomes across a wide variety of contexts. To pursue these learning objectives, we overcome the data and identification challenges inherent to investigating bribery: we build an original dataset on Tunisian customs transactions using an audit study to directly observe bribes, and we leverage a natural experiment in which a computer algorithm randomly assigns customs officials to import shipments. There are three sets of results. First, we show that bribery and tax evasion are widespread, that bribery is collusive (not coercive), and that age (but not gender) predicts officials' corruptibility. Second, in line with a straightforward Nash bargaining model, we show that the length of official/trader relationships increases tax evasion but decreases bribe amounts. Third, we zoom out to consider the larger macroeconomic implications and show that, in terms of lost tax revenue, bribery costs the Tunisian government 0.7% of GDP or $80 per citizen.

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1 Introduction

Every year low- and middle-income countries (LMICs) import goods worth more than $7 trillion (UN, 2021). In some states the process runs smoothly, but in many others shipments of everything from airplanes to bananas must first pass through the hands of corrupt customs officials (Svensson, 2005). This corruption likely has first-order welfare implications. International trade can drive economic growth by diffusing technological innovations and rewarding productive firms; it can generate a nontrivial share of LMICs' tax revenues; and it can provide the global poor with cheaper goods and lifesaving necessities - as the distribution of vaccines during the COVID-19 pandemic has made clear (Acemoglu, 2009; Gordon and Li, 2009). With such high stakes, policymakers require a deep understanding of both the causes and the effects of customs fraud.

In addition, researchers have the opportunity to use trade corruption as a laboratory to discover new insights about corruption as a whole. One previously unexplored complexity is that bribe payers and bribe receivers often have repeated interactions: just as traders at airports and seaports face the same customs officials on shipment after shipment, many truck drivers find the same police officers always assigned to their routes, and many restaurant owners find the same health inspectors always assigned to their neighborhoods. Given corruption's characteristic contracting frictions, counterparty risks, and information asymmetries, these long-running relationships likely matter for a wide variety of outcomes across a wide variety of contexts.

To pursue these general learning objectives, we focus on three specific research questions: Are bribery relationships "coercive" (where officials extort traders) or "collusive" (where officials and traders partner to evade taxes), and which officials are more likely to participate in this abuse of power? How do officials and traders bargain over the bribe and tax-evasion amounts, and how does their bargaining change with an increase in the number of times that they have worked together in the past? What are the macroeconomic implications of this corruption for equilibrium trade volume and tax revenue?

Answering these questions requires overcoming the data and identification challenges inherent to investigating bribery. One problem is the trouble with acquiring data on illegal and secretive behavior. To solve this problem, we build an original dataset on Tunisian customs transactions using an audit study to directly observe bribery. Audit studies allow researchers to measure real-time, fine-grained details on clandestine actions. Economists have used audit studies in environments ranging from D.R. Congo to Indonesia, but to our knowledge ours is the largest to date in the international-trade sector and the first in the Middle East and North Africa. Overall, our dataset contains trade, taxation, and bribery information on thousands of transactions across hundreds of shipments. In addition, since Tunisia is in many ways a typical middle-income country (whose income *per capita* is halfway between Nigeria's and Brazil's), we believe the patterns in our data are likely to be representative beyond Tunisia's borders.

Another problem is that the factors giving rise to bribery are unlikely to be randomly assigned. This means that it is often hard to disentangle whether various characteristics are actually causing different corrupt behavior or merely correlated with different corrupt behavior. For example, if higher-ranked officials happen to take more bribes, then it would not be clear whether having a higher rank makes officials more corrupt intrinsically or if higher-ranked officials are just more likely to interact with more corrupt traders. To solve

this problem, we leverage a natural experiment in which a computer algorithm randomly assigns customs inspectors to import shipments. The randomization allows us to more credibly estimate the models we use to answer some of our main research questions, as we describe in detail below.

There are three sets of results. First, we characterize the nature of seaport bribery and tax evasion. We show that bribery and tax evasion are widespread: 57% of transactions involve illicit money changing hands. We show that the dollar values are nontrivial: the average bribe amount is $719, and the average amount of taxes evaded is $1,202. And we show that bribery is collusive, not coercive: traders have the choice to pay less than what they owe in taxes by participating in bribery. In addition, we determine which types of officials tend to abuse their power. Using our natural experiment, which amounts to a judge-leniency design (Kling, 2006), we find that on the one hand younger officials are less likely to accept bribes, but on the other hand they facilitate higher levels of tax evasion when they do accept bribes. We also find, contrary to previous evidence, that female officials are no more or less corrupt than their male colleagues (Dollar et al., 2001; Decarolis et al., 2022).

Second, we analyze negotiations over bribery and tax evasion embedded within dynamic official/trader relationships. We build a game theory model to formalize our thinking and develop testable implications. The model is a straightforward Nash bargaining model that, with only one additional set of assumptions, generates counterintuitive hypotheses consistent with our data. As the length of official/trader relationships increases, trust increases, risk decreases, and they engage in more tax evasion. However, the effect on bribes is ambiguous, since what matters is not risk *per se* but the change in the risk differential between the two players. Using this model and our natural experiment, we find that the length of official/trader relationships increases tax evasion but decreases bribes. We also use measures of trust and risk to provide evidence on mechanisms.

Third, we zoom out to consider the larger macroeconomic implications of bribery and tax evasion in international trade. Our data shows that on average each shipment sees 13% of taxes evaded, so one might conclude that in the aggregate the Tunisian government is losing 13% of its port tax revenue. But such a conclusion would not account for traders' demand response: if bribery affects the effective tax rate, then it likely affects overall trade volume too. To account for this equilibrium response, we use calibrated import-demand elasticities to perform a back-of-the-envelope calculation of bribery's effect on state fiscal capacity. Our preferred estimate is that bribery costs the Tunisian government 0.7% of GDP or $80 per citizen.

These three sets of results together make a number of contributions. We most directly contribute to the literatures on trade corruption (Chalendard et al., 2019, 2021; Fisman and Wei, 2004; Rijkers et al., 2014, 2017; Sequeira and Djankov, 2014; Yang, 2008) and corruption dynamics (Amodio et al., 2018; Campante et al., 2009; Dal Bo and Rossi, 2011; Macchiavello and Morjaria, 2015; Niehaus and Sukhtankar, 2013; Olken and Barron, 2009; Sanchez de la Sierra, 2020). We also contribute to several other corruption sub-literatures. In terms of theory, we complement a body of work on the methods of bargaining between bribe payers and bribe receivers (Khan et al., 2016). In terms of empirics, we complement a body of work showing that bribery is a net cost for emerging markets (Amodio et al., 2018; Colonnelli and Prem, 2021; Fisman and Svensson, 2007; Shleifer and Vishny, 1993). And in terms of methodology, we break ground by running an audit study in a new setting

(Olken and Barron, 2009; Sanchez de la Sierra and Titeca, 2017; Sequeira and Djankov, 2014). Specifically, while most past studies of bribery in international trade have used indirect metrics, such as estimation-by-subtraction techniques that compare the value of imports (which face a tax-evasion incentive) to the value of exports (which do not), ours is only the second study of which we are aware that directly observes bribery in customs transactions.

We also speak to certain other policy-relevant fields of economics. By focusing on how bribery affects trade volume, we contribute to trade economics (Kee et al., 2008; Tokarick, 2010); to our knowledge, our study is the first to marry empirical estimates of bribery and tax evasion at seaports with trade elasticities to credibly estimate corruption's equilibrium effect on international trade. By focusing on how bribery affects tax revenue, we contribute to the public finance of development (Basri et al., 2019) and to "institutions" growth macroeconomics (Acemoglu, 2009); these studies tend to show that higher state fiscal capacity is a strong predictor of faster development, which underlines the welfare implications of our findings. In addition, our results on which types of officials are corruptible contribute to the personnel economics of the state (Finan et al., 2015).

The paper proceeds as follows. Section 2 describes our Tunisian context. Section 3 describes our data. Section 4 analyzes seaport bribery and tax evasion, including the coercive/collusive margin and officials' corruptibility. Section 5 analyzes repeated bargaining. Section 6 analyzes the macroeconomic implications. Section 7 concludes.

2 Context

2.1 Tunisian Customs Transactions

There are three facts essential for understanding Tunisian customs transactions, all of which have parallels to other ports around the world. First, a number of actors touch each shipment, either directly or indirectly. On one end is the firm that bought the shipment on the international marketplace. On the other end are the customs officers who clear the shipment and who fall into two categories: "liquidateurs" have primary responsibility for clearing shipments, while "reviseurs" review their liquidateur colleagues' work. (Think of the distinction as like that between the immigration official who stamps your passport and the one who checks for your stamped passport at the exit.) In the middle is the trader,[1] whose client is the firm and whose job is to intermediate between the firm and the customs officials; traders' business models vary, but in general they are responsible for managing all interactions with customs, with the shipping companies, and with other port employees. Finally, there are stevedores who move the goods from the ships to different areas around the port and eventually to the traders' trucks.[2] Figure 1 visualizes the connections these actors have to the shipment and to each other.

Second, the clearance process has a number of steps. Shipments arrive by ship and wait to be cleared by customs, usually within one to a few weeks. During the waiting process, sometimes shipments stay at the port, and sometimes they move to warehouses owned

[1] Tunisians call traders "transitaires."

[2] Tunisians call stevedores "STAM" workers.

by the traders' clients but guarded by customs officials. The clearance itself involves inspecting the goods, inspecting the paperwork, and/or collecting the taxes; the intensity of these steps depends on the "lane" to which the goods are assigned, with the red, orange, and green lanes running from more to less intensive.

Third, the Tunisian customs administration uses a computer algorithm to randomly assign officials to shipments. We have done numerous focus groups with traders and retired officials to learn more about how this computer algorithm works. To our knowledge, when a shipment arrives at the port, it is assigned to one of the set of available officials, with equal probability and unconditional on any descriptive characteristics.

2.2 Tunisia's Political Economy

In Tunisia, bribery has long been quotidian (Yerkes and Muasher, 2017). One of the motivations for the 2010-2011 protests that toppled dictator Zine Abidine Ben Ali was a concern with the corruption that had come to characterize his regime. Investigations conducted following Ben Ali's 2011 removal have revealed the customs administration to be one of the main sites in which this corruption took place. Reports published by Tunisian state institutions (National Commission for Investigations of Bribery and Corruption, 2011; Truth and Dignity Commission, 2019) and academic researchers (Rijkers et al., 2017) have detailed the ways that associates of Ben Ali manipulated the declaratory system to evade taxes or secure other advantages.

The political transition precipitated by Ben Ali's removal allowed for some anti-corruption reforms. Authorities have periodically either arrested or forced the retirement of officials suspected of bribery.[3] In 2018 the customs administration began to employ cameras at a number of its facilities, and in 2019 it began to require customs officials to wear photo identification. Also in 2019, the customs administration announced a five-year strategic plan focused in part on establishing integrity and transparency, and it received an award by the anti-corruption commission (INLUCC) for its progress in combating corruption.

But many Tunisians believe that the customs administration remains extremely corrupt, with many raising the prospect that it has in fact worsened during the transition. A December 2020 corruption-perceptions survey fielded by INLUCC asked respondents to name the institutions in the country most afflicted by corruption; more respondents (53%) named the customs administration than named any other institution outside of the security sector. Asked to specifically evaluate the level of corruption in the customs administration, approximately 90% estimated it to be a serious problem (GIZ and INLUCC, 2020). Some Tunisian elites have hypothesized a "democratization of corruption" after the revolution, meaning a spread beyond the groups that were close to Ben Ali. Academic research on tax evasion before and after the ouster of Ben Ali suggests that corruption remains serious

[3] In 2017, then-prime minister Youssef Chahed announced the beginning of a "war on corruption" starting with the arrest of customs official Colonel Ridha Ayari, along with three businessmen. In May 2020, the government announced the forced retirement of 21 customs officials suspected of engagement in corruption. In June 2020, the national anti-corruption commission (INLUCC) referred a captain in the customs administration for prosecution when it discovered that he had acquired a number of real-estate holdings. In December 2020, the minister of the environment and a number of others, including a high-level customs official, were arrested for their alleged involvement in a *quid pro quo* allowing the illegal importation of 282 containers filled with municipal waste from Italy.

- and has perhaps worsened. Indeed, Rijkers et al. (2017) find tariff evasion to have increased overall, even if its practice by those who were politically connected to Ben Ali has not.

Finally, bribery is consequential to the economy. The customs administration claims to contribute one quarter of all tax revenue collected by the Tunisian state, but Rijkers et al. (2014) and Rijkers et al. (2017) show that the corrupt practices of politically connected firms during the Ben Ali regime harmed market competition and tax collection. The qualitative work we did at the start of this project is consistent with this literature. For example, we spoke with a Tunisian businessman who currently imports pool chemicals and used to import mopeds. He went out of business as a moped-importer because his competitors were selling their goods at a markdown that they could only afford by engaging in bribery-facilitated tax evasion. He decided to pivot to the market with the highest-margin tariff-free goods so that he would be protected against corrupt competitors, and that market turned out to be pool chemicals. Similarly, ICG (2017) includes an interview with a smuggler who was dissuaded from engaging in the legal vegetable trade with Algeria by a customs official who preferred that the two collude in the illegal import of donkeys.

3 Data

3.1 Audit-Study Data

We build an original dataset on Tunisian customs transactions using an audit study to directly observe bribery, to our knowledge the largest to date in the international-trade sector and the first in the Middle East and North Africa.

The benefit of audit studies is that they allow researchers to measure real-time, fine-grained details on individual clandestine actions. For example, Olken and Barron (2009) hire Indonesian truck drivers to measure bribes at military checkpoints; Sanchez de la Sierra and Titeca (2017) hire Congolese bus riders to measure bribes to traffic police; and Sequeira and Djankov (2014) hire Southern African traders to measure bribes in customs transactions. In our case, our dataset contains 1,968 shipments processed between November 2019 and June 2021,[4] with information on the shipment itself, the trader, the trader's client, the customs officials who interact with the trader, legal characteristics of the transaction (e.g., taxation), and illegal characteristics of the transaction (e.g., bribery). To build such a dataset, we recruited 18 traders to complete surveys on their shipments shortly after clearance.[5]

Consideration for the participating traders' well-being informed all aspects of the data-collection process. To compensate them for their time and effort, we provided the traders with financial payments for every survey they completed, as well as every interview and training they attended.[6] To mitigate the liability they faced from disclosing evidence of

[4]The data we focus on in this paper comes from Q1-Q2 2021. That is the period after which we made updates to the survey that allowed us to observe the random assignment of officials to shipments and which allowed us to solve a problem related to the accidental over-reporting of certain product values and tax payments. See Table A9 for selected results using our whole dataset.

[5]The vast majority of our data comes from ten of these 18 traders.

[6]For the majority of the study we limited each trader to completing ten surveys per every two-week

unlawful actions, we also provided the traders with a letter from the Tunisian Institute for Strategic Studies (ITES), a think tank within the Tunisian president's office and our official study partner, offering them *de facto* legal protections. Furthermore, because we judged a breach of confidentiality to be the greatest risk to the participants, we avoided collecting any personally identifiable information, issued them code names (in the form of car brands, as seen in Figure 2), and created a firewall between participant- and data-facing members of the research team (researchers involved in obtaining consent, training participants, or liaising with them throughout the study did not have access to the data; researchers involved in analyzing the data did not have access to participants). Finally, although we initially allowed participants the option to use paper questionnaires, at the start of the COVID-19 pandemic we adopted exclusively digital and contactless procedures.[7]

To recruit our traders, we used a combination of random and snowball sampling. We obtained a list of all registered traders in Tunisia from the customs offices' public record, randomly selected names from the list, and called them asking them to participate. This method was fruitful, but imperfect: many of the names and much of the contact information was out of date, and the majority of traders in Tunisia are unregistered/informal. (Many even illegally "rent" credentials from retired or deceased traders.) To complement this sample, we also asked well-established traders to make an approach on our behalf to some of their colleagues. Overall, while our sample of traders might or might not be representative, we view our recruitment strategy as strictly dominant over the social-science practice of persuading only one firm (versus, in our case, 18) to share proprietary data.

3.2 Administrative Data

To complement our survey data, we also acquired two sources of administrative data. First, a subset of traders shared documentation called a "Declaration en Detail des Merchandises" (DDM). Traders share relevant information about their shipments with the customs administration using a web interface, and the DDM is a one-page readout of that information. It contains the declared goods, the declared value, the taxes collected, and a number of other variables. Because of concerns for the confidentiality of the traders and their clients, we avoided collecting DDMs from shipments during the time period of our audit study. Instead, several traders shared DDMs from shipments during earlier time periods, for which we therefore do not have any corresponding information about criminal activities.

Second, we downloaded open-source data on Tunisian international trade published by the Tunisian government and certain IGOs like the OECD, the WTO, and the World Bank. These data contain important variables such as the country's total annual trade volume and trade tax revenues collected through tariffs and VATs.

period; without this limit IRB was concerned that participating in the study could become a meaningful source of revenue for the traders, thus potentially distorting their behavior.

[7] We paused the study at the onset of the pandemic. Once the traders had already gone back to working in-person at the port, in consultation with them and with IRB, we resumed the study using digital and contactless procedures to collect data and compensate participants.

3.3 Data Quality

A shortcoming of audit studies is that it is difficult to ensure data quality. One might be concerned, for example, that traders would feel uncomfortable revealing whether they had engaged in bribery, leading to an underestimate of its propensity. Reassuringly, Figure 2 shows that most of the participants in the study did reveal engaging in bribery at least once in a while. Furthermore, it seems likely that traders would be more likely to lie about *whether* they pay bribes than about the *amount* of the bribes they pay, so our confidence in the extensive-margin data gives us confidence in the intensive-margin data.

To further confirm the validity of the numbers in our surveys, we use the DDMs described above; although these declarations are not a random sample, they nonetheless give us benchmarks. We therefore adopt three criteria for dropping data of dubious quality. We drop observations for which either the product value or the tax owed was more than ten times the maximum among DDMs. We drop observations for which the tax owed is more than three times that of the product value (i.e., for which the reported tax rate is more than 300%). And we drop observations for which the reported tax paid is more than two times the tax owed.[8]

On the flip side, there are some patterns in the data that speak in favor of its quality, as we can see in Table 1. The median shipment in the dataset has a reported product value of approximately $32,062 and a reported tax liability of $7,027. This amounts to a tax rate of approximately 19%, which exactly matches the value-added tax rate of 19% applied to most goods imported by Tunisia (International Trade Administration, 2020). 18% of the officials in our sample are female, which is very similar to the 20% reported by the customs administration, and there is a strong correlation between officials' reported ages and their reported ranks.

In addition, the majority of shipments (53.6%) originated in the European Union, with large proportions also coming from Turkey (14.7%), China (11.2%), other parts of Europe (9.3%), or other parts of Asia (6.7%). By value, the proportion of the shipments originating in each region is largely reflective of Tunisian imports, although it slightly over-represents shipments originating in Turkey and Asia and underrepresents those originating in the EU or elsewhere in the Arab world.[9]

4 Seaport Bribery & Tax Evasion

4.1 Bribery & Tax Evasion

Table 2 shows further descriptive statistics on Tunisian customs transactions.

Tax evasion is widespread. The mean shipment owed $8,853 in taxes but paid only $7,651

[8] In our 1968-N dataset, 185 observations exceeded at least one of these thresholds, most commonly due to an unusually large product value. These observations were concentrated in the early periods of the study. Only six observations included in the most recent period of the study exhibited questionable quality, according to these criteria.

[9] The under-representation of shipments from the Arab world should not be surprising since our data collection happened at seaports whereas many goods from Algeria and Libya enter through Tunisia's land borders.

in taxes. This amounts to $1,202 stolen per shipment, or an evasion rate of 13% (1 minus the 87% in the table). One shipment stole as much as $14,400.[10]

Bribery is widespread too. 57% of transactions saw a bribe change hands, and the median bribe amount in those transactions was $540. One bribe was as much as $30,394.[11]

4.2 Coercion versus Collusion

Frequency and magnitude are only two of the three most important ways to categorize bribery. It is also important to know whether the bribery is coercive or collusive. Under coercion, the official uses their power to extort the trader into paying a bribe over and above the tax owed. The official says something like, "I see that the tax owed is $100. But pay me $120 or else I'll find a pretext to delay your clearance or confiscate your goods." The following equation generalizes this example.

$$\text{Tax Paid} = \text{Tax Owed} + \text{Official's Bribe}$$

Under collusion, the official and the trader work together to find a mutually beneficial way to evade taxes. The official says something like, "I see that the tax owed is $100. Let's forge new paperwork, only pay $60, and split the $40 profit 50/50." The following equation generalizes this example.

$$\text{Tax Owed} = \text{Tax Paid} + \underbrace{\text{Tax Evaded}}_{=\text{Trader's Profit}+\text{Official's Bribe}}$$

In both of these cases, the bribe is the same amount, but the welfare implications are very different. Compared to the legal baseline, coercive bribery is beneficial to the official but costly to the trader; collusive bribery is beneficial to the official and the trader, but costly to the traders' competitors and to the government collecting the taxes.[12]

Within this framework, the evidence shows that bribery in Tunisian customs transactions is decidedly collusive. Table 3 is a pivot table showing the percentage breakdown of transactions by when they have a bribe and when they evade taxes. We can see that approximately 42% neither bribe nor evade taxes,[13] and approximately 53% both bribe and evade taxes; in other words, a total of approximately 95% are characterized by what we might call "discretionary collusion," where the risk-tolerant officials and traders can evade taxes while the risk-averse can opt out. Only approximately 4% involved bribery without tax evasion (coercion), and less than 1% featured tax evasion without bribery (crime).

[10] Our survey asks separately about the tax *owed* and the tax *paid*.

[11] Since the maximum bribe amount is greater than the maximum tax-evasion amount, the bribe must have been coercive. See below.

[12] For both types, there are also likely implications for firms deciding to enter or exit the market.

[13] We do not observe large differences in clearing times between shipments with and without bribes, suggesting that officials do not use the threat of delays to extort coercive bribes. See Figure A1.

We can also visualize this relationship graphically. Figure 3 is a scatter plot with bribery amounts on the x-axis and tax-evasion amounts on the y-axis (where a positive number means over-paying and a negative number means under-paying).[14] The data points clustered at the origin reveal the legal transactions without any bribery or tax evasion. The data points in the first quadrant reveal the collusive transactions with both bribery and tax evasion - and the implied slope greater than one suggests we can think of the bribe as the official's share of the tax evasion. If there had been many data points clustered along the horizontal axis, they would have revealed coercive transactions with bribery but no tax evasion.

Similarly Figure 4 is a kernel density plot showing taxes paid and owed, both with bribery and without bribery. We can see that the distribution of taxes paid and owed without bribery are on top of each other, whereas the distributions with bribery are shifted relative to each other, thus revealing clear tax evasion.

That bribery is more commonly an instrument of tax evasion than of official extortion is also apparent from answers to a direct question in the survey. Figure 5 shows that, when asked why they paid a bribe, more than 60% of traders reported that the official would let them evade some tax or regulation. Meanwhile, less than 5% of traders reported that they had paid a bribe because they feared the official would punish them otherwise. Figure 6 shows that, among those who reported paying a bribe to avoid taxation or regulation, large percentages reported doing so by misreporting the shipment's weight or value.

Our collusion finding is consistent with previous scholarship on bribery in the Tunisian customs administration. Hibou (2011) argues that allowing widespread tax evasion was a mechanism for the Ben Ali regime to discipline potential opponents by making them complicit. Similarly, the investigation by the Truth and Dignity Commission points to under- or mis-reporting of the contents of shipping containers as the primary means by which firms engaged in corruption. Finally, Rijkers et al. (2017) calculate "evasion gaps" at Tunisia's ports. Although each of these studies focuses on the period before the Arab Spring, our research suggests that collusive bribery remains far more common than coercive bribery.

4.3 Officials' Corruptibility

4.3.1 Summary

In addition to characterizing *how* bribery works, we can also characterize *who* gets bribed. The purpose of this section is to determine whether easily observable demographic characteristics (ones that the customs-office management has access to) can predict which types of officials tend to abuse their power. We find that age does predict officials' corruptibility but that gender does not.

4.3.2 Estimation Strategy

For each trader i, official j, time k, and shipment l, our two outcomes of interest are the presence of a bribe $1\{b \neq 0\}_{ijkl}$ and the tax paid t_{ijkl}. Let x_{jk} be one of two demographic

[14] See also Figures A2-A3.

characteristics of the official, either the decade of age a_{jk} or an indicator for being female f_j. Let λ_k be time fixed effects.[15] Let U_{jk} be a vector of other official-level controls (e.g., age, gender, and rank).[16] Let V_{ijkl} be a vector of shipment-level controls (e.g., tax owed) that our balance regression in Table A1 says are, despite random assignment, predictive of demographic characteristics.

With these variable definitions, our regression specification is as follows, with the βs are our coefficients of interest.

$$1\{b \neq 0\}_{ijkl} = \alpha^b + \beta^b x_{jk} + \gamma^b U_{jk} + \delta^b V_{ijkl} + \lambda_k^b + \epsilon_{ijtk}^b$$
$$ln(t_{ijkl}) = \alpha^t + \beta^t x_{jk} + \gamma^t U_{jk} + \delta^t V_{ijkl} + \lambda_k^t + \epsilon_{ijtk}^t$$

Because of our natural experiment, the βs have a causal interpretation, but it is worth making a subtle distinction. Suppose we had found that officials with blue eyes were more corrupt. On the one hand, since demographic characteristics like blue eyes are not themselves randomly assigned, there could be omitted variable bias, so it would be incorrect to say that blue eyes cause corruptibility. (Maybe people with blue eyes are less honest.) On the other hand, we are not interested in the true "structural relationship" between iris pigment and port operations; we are interested in providing the type of information that government H.R. managers and anti-corruption auditors could use to tell which officials are more or less likely to abuse their office. To that end, our specification is in fact capable of saying causally that putting an official with blue eyes in charge will lead to a more corrupt portfolio.

In other words, random assignment of inspectors is useful because it eliminates the possibility that certain characteristics are correlated with bribery and tax evasion merely because of how individuals happened to self-select into working together.

4.3.3 Results

Figures 7-8 and Table 4 show the results of these econometric tests. Figure 7 contains bar plots showing the probability of bribery for different types of officials. Figure 8 contains kernel density plots showing the distributions of bribe amounts for different types of officials. Table 4 shows regression estimates using the econometric specification described above.

First, we can see that each additional decade of age increases the probability of accepting a bribe by 1.6 percentage points. This finding is consistent with many mechanisms. It could be selection, in which less corrupt officials quit or get fired for not being team players. It could be treatment, in which over time corruption gets normalized or officials learn how to be more corrupt. It could also be a cohort effect, with younger generations coming of age since the revolution and therefore being more committed to good government. Interestingly, though on the extensive margin older officials are more likely to steal, when they do, they steal less. We can see that each additional decade of age increases taxes paid by 1.1 percentage points.

[15] Our results are not robust to trader fixed effects. See Table A4.
[16] Table A3 shows additional controls.

Second, we can see that female officials are no more or less corrupt than their male colleagues, in terms of both whether they steal and how much they steal. This finding is inconsistent with a stylized fact from other studies saying that females are less corrupt than males. This could be due to selection into becoming a customs officer, where less corrupt females are screened out.

5 Repeated Bargaining

5.1 Game Theory Model

5.1.1 Summary

The purpose of this model is twofold. First, it formalizes our thinking about bribery negotiations as fundamentally about bargaining over the surplus of tax evasion, mediated by risk and trust. Second, the model generates testable implications and structures the reduced-form econometrics we describe below.

Overall, we build off of Nash (1950) and Khan et al. (2016) to structure a model that, while static, is still able to generate insights on dynamic bargaining. With only one additional set of assumptions, our model generates counterintuitive hypotheses confirmed by the data: repeated interactions increase trust, decrease risk, increase tax evasion, and may *either increase or decrease* bribery. In other words, it is possible for bribes to go down even as tax evasion goes up.

5.1.2 Setup

There is a trader and an official who use bribery to bargain over tax evasion. The taxes owed $\tilde{t}$ is an exogenous parameter, while the taxes paid t and the bribe b are endogenous variables that the two players optimize. Their utilities $U_T(t, b; \tilde{t})$ and $U_O(t, b; \tilde{t})$ depend on whether they do engage in tax evasion $1\{t \neq \tilde{t}\}$ or do not engage in tax evasion $1\{t = \tilde{t}\}$.

$$U_T(t, b; \tilde{t}) = U_T^0(t, b; \tilde{t}) \times 1\{t = \tilde{t}\} + U_T^1(t, b; \tilde{t}) \times 1\{t \neq \tilde{t}\}$$
$$U_O(t, b; \tilde{t}) = U_O^0(t, b; \tilde{t}) \times 1\{t = \tilde{t}\} + U_O^1(t, b; \tilde{t}) \times 1\{t \neq \tilde{t}\}$$

If they do not engage in tax evasion $1\{t = \tilde{t}\}$, then the trader's utility $U_T^0(t, b; \tilde{t})$ is decreasing in taxes owed $\tilde{t}$; the official's utility $U_O^0(t, b; \tilde{t})$ is zero.

$$U_T^0(t, b; \tilde{t}) = -\tilde{t}$$
$$U_O^0(t, b; \tilde{t}) = 0$$

If they do engage in tax evasion $1\{t \neq \tilde{t}\}$, then the trader's utility $U_T^1(t, b; \tilde{t})$ is decreasing in taxes t, decreasing in the risk of tax evasion (a quadratic cost-of-risk function of the

tax owed $\tilde{t}$ less the tax paid t mediated by the parameter $\alpha > 0$), and decreasing in the bribe b; the official's utility $U_O^1(t, b; \tilde{t})$ is decreasing in the risk of tax evasion (a quadratic cost-of-risk function of the tax owed $\tilde{t}$ less the tax paid t mediated by the parameter $\beta > 0$), and increasing in the bribe b.

$$U_T^1(t, b; \tilde{t}) = -t - \alpha(\tilde{t} - t)^2 - b$$
$$U_O^1(t, b; \tilde{t}) = -\beta(\tilde{t} - t)^2 + b$$

The two play a static Nash bargaining game where they bargain over the joint surplus of tax evasion $S(t; \tilde{t})$. As a first step, they calculate the tax-evasion amount that maximizes their joint surplus; specifically, the equilibrium tax paid t^* (which, since $\tilde{t}$ is exogenous, automatically determines the tax-evasion amount) is just what maximizes the joint surplus. As a second step, they calculate the bribe that optimally splits the joint surplus; specifically, the equilibrium bribe b^* is what maximizes the so-called Nash product (defined as the product of the differences in the two players' utilities between the two states of the world) evaluated at t^*.

$$\begin{aligned}
S(t; \tilde{t}) &= (\tilde{t} - t) - \alpha(\tilde{t} - t)^2 - \beta(\tilde{t} - t)^2 \\
\Rightarrow \frac{\partial S(t^*; \tilde{t})}{\partial t} &= 0 \\
\Rightarrow t^* &= \tilde{t} - \frac{1}{2}\frac{1}{\alpha + \beta} \\
b^* &= \text{argmax}[U_T^1(t^*, b; \tilde{t}) - U_T^0(t^*, b; \tilde{t})][U_O^1(t^*, b; \tilde{t}) - U_O^0(t^*, b; \tilde{t})] \\
\Rightarrow \frac{\partial[U_T^1 - U_T^0][U_O^1 - U_O^0]}{\partial b} &= 0 \\
\Rightarrow b^* &= \frac{\alpha + 3\beta}{8(\alpha + \beta)^2}
\end{aligned}$$

Intuitively, using the Nash product is equivalent to choosing a bribe such that the two players' utilities with tax evasion are the same as their utilities without tax evasion (their "outside options") plus one half of the joint surplus evaluated at t^* and b^*.[17][18][19]

[17] See the Appendix for a proof.

[18] Note that the joint surplus is denominated in utility, not money, so the official receiving one half of the joint surplus does *not* necessarily imply that the official's bribe is one half of the tax-evasion amount.

[19] This Nash bargaining solution (NBS), which is economists' workhorse model for analyzing negotiation, yields a 50/50 split of the surplus because it implicitly assumes "symmetry" between the two players. However, it is possible to extend the model to an asymmetric Nash bargaining solution (ANBS) that would yield a generic $\gamma/(1-\gamma)$ split of the surplus by adding exponents to the Nash product (such that that Nash product would become $(...)^{\gamma}(...)^{1-\gamma}$). We opt for the NBS because it is more standard, it minimizes degrees of freedom, and differential preferences over the feasibility set are already enough to account for differential bargaining power (Kariv, 2009).

$$
\begin{aligned}
U_T^1(t^*, b^*; \tilde{t}) &= U_T^0(t^*, b^*; \tilde{t}) + \gamma S(t^*; \tilde{t}) \\
U_O^1(t^*, b^*; \tilde{t}) &= U_O^0(t^*, b^*; \tilde{t}) + (1-\gamma) S(t^*; \tilde{t}) \\
\text{s.t. } \gamma &\equiv 1 - \gamma \equiv \frac{1}{2}
\end{aligned}
$$

One implication is that taxes paid are increasing in the sum of α and β; intuitively, tax evasion is decreasing in aggregate risk. Second, bribes are decreasing in α, since the higher the risk to the trader, the more the official has to compensate her with a lower bribe. Third, bribes are either increasing or decreasing in β, depending on a numerical threshold. On the one hand, the higher is β, the higher is the risk to the official and the more the trader has to compensate her with a higher bribe. On the other hand, the higher is β, the lower the tax-evasion amount and the less money there is to go into the bribe.

$$
\begin{aligned}
\frac{\partial t^*}{\partial \alpha} &= \frac{1}{2(\alpha+\beta)^2} > 0 \\
\frac{\partial t^*}{\partial \beta} &= \frac{1}{2(\alpha+\beta)^2} > 0 \\
\frac{\partial b^*}{\partial \alpha} &= \frac{-\alpha - 5\beta}{8(\alpha+\beta)^3} < 0 \\
\frac{\partial b^*}{\partial \beta} &= \frac{\alpha - 3\beta}{8(\alpha+\beta)^3} > 0 \Leftrightarrow \alpha > 3\beta \\
\frac{\partial b^*}{\partial \beta} &= \frac{\alpha - 3\beta}{8(\alpha+\beta)^3} < 0 \Leftrightarrow \alpha < 3\beta
\end{aligned}
$$

So far the setup is the same as Khan et al. (2016), except we have quadratic cost instead of linear cost. Making the function differentiable allows for a continuous set of tax evasion amounts, which is a pattern we see in our data.

5.1.3 Matches, Trust & Risk

Within this setup, we make only one additional nested assumption: risk α and β are decreasing functions of trust u, which is itself an increasing function of matches m.

$$
\begin{aligned}
\frac{\partial u(m)}{\partial m} &> 0 \\
\frac{\partial \alpha(u(m))}{\partial u(m)} &< 0 \\
\frac{\partial \beta(u(m))}{\partial u(m)} &< 0 \\
\Rightarrow \frac{\partial \alpha(u(m))}{\partial m} &= \alpha' < 0 \\
\Rightarrow \frac{\partial \beta(u(m))}{\partial m} &= \beta' < 0
\end{aligned}
$$

This assumption is motivated by both our natural experiment and our many focus groups with traders and retired officials. First, these individuals say that trust and risk are central to their interactions with each other. For example, one trader said, "The more transactions [the trader and the official] have together, the stronger the relationship becomes. So, there is trust between them.[20] Second, the traders conceptualize matches as exogenous, backward-looking variables, not endogenous, forward-looking variables. This is why the model treats matches as a state variable that the two players take as given in each independent stage game.[21]

It follows automatically from this assumption that taxes paid are decreasing in matches and therefore tax evasion is increasing in matches.

$$
\frac{\partial t^*(\alpha(u(m)), \beta(u(m)))}{\partial m} = \frac{(\alpha' + \beta')}{2(\alpha + \beta)^2} < 0
$$

One might think that an increase in tax evasion automatically implies an increase in the bribe. If the pie gets bigger, then it seems natural for the pieces of the pie to get bigger too. In fact, the model has an ambiguous prediction about the relationship between bribes and taxes.[22]

$$
\begin{aligned}
\frac{\partial b^*(\alpha(u(m)), \beta(u(m)))}{\partial m} &= \frac{1}{8(\alpha + \beta)^3}[\alpha'(-\alpha - 5\beta) + \beta'(-\alpha + 3\beta)] \\
\Rightarrow \frac{\partial b^*(\alpha(u(m)), \beta(u(m)))}{\partial m} &> 0 \Leftrightarrow \alpha < 3\beta \cup \frac{\beta'}{\alpha'} < \frac{\alpha + 5\beta}{\alpha - 3\beta} \\
\Rightarrow \frac{\partial b^*(\alpha(u(m)), \beta(u(m)))}{\partial m} &< 0 \Leftrightarrow \alpha > 3\beta \cap \frac{\beta'}{\alpha'} > \frac{\alpha + 5\beta}{\alpha - 3\beta}
\end{aligned}
$$

[20] One alternative would have been to model trust as affecting utility, not indirectly through risk, but directly through social preferences.

[21] One alternative would have been to model an extensive-form game in which the players have subjective beliefs about future matches and use backward induction to arrive at a subgame perfect equilibrium. Such a model would be a less parsimonious representation of our context and would add unnecessary complexity.

[22] See the Appendix for a proof.

Intuitively, this two-part condition says that two factors matter for whether bribes are increasing or decreasing in matches: (1) whether bribes are increasing or decreasing in the β and (2) whether the effect of β on bribes or the effect of α on bribes is stronger.

First, recall that bribes are either increasing or decreasing in β. On the one hand, the official's risk puts upward pressure on the bribe because of risk compensation. On the other hand, the official's risk puts downward pressure on the bribe because risk decreases the joint surplus from tax evasion. $\alpha - 3\beta$ is the threshold that governs this tradeoff, so it makes sense that it would reappear here. Since β is decreasing in matches, if bribes are increasing in β, then matches put downward pressure on the bribe, but if bribes are decreasing in β, then matches put upward pressure on the bribe.

Second, in the latter case, there is a "competition" between the rate of change in the risk differential between the two players, β'/α'. On the one hand, matches decrease β, which puts downward pressure on the bribe. On the other hand, matches decrease α, which puts upward pressure on the bribe. $(\alpha + 5\beta)/(\alpha - 3\beta)$ is the threshold that governs this tradeoff.

Consider an example of this competition. Suppose an official and a trader match for the first time on a shipment that owes \$100 in taxes. And suppose their risk parameters are such that they decide to pay only \$80, evade the other \$20, and split the surplus 50/50, generating a bribe of \$10. Suppose they match together for a second time, now with higher trust and therefore lower risk. Their new risk parameters are such that they pay only \$60 and evade the other \$40, but they do not automatically agree on another 50/50 split. If the risk to the official has gone down more than the risk to the trader, then the official will have to compensate the trader for that risk. The new split could be 40/60, resulting in a higher bribe, 25/75, resulting in the same bribe, or 20/80, resulting in a lower bribe. All three scenarios, and many more, are possible, since the official prefers a lower bribe amidst higher tax evasion to the outside option of getting nothing at all.[23]

Figures 9-11 visualize examples with a 50/50 split, uneven splits, and a split that is so uneven that tax evasion and bribery diverge.

5.1.4 Testable Implications

We take the following three testable implications to the data.

$$\frac{\partial u}{\partial m} > 0 \tag{1}$$

$$\frac{\partial t^*}{\partial m} < 0 \tag{2}$$

$$\frac{\partial b^*}{\partial m} \neq 0 \tag{3}$$

[23]Note that, whether or not the trader and the official split the *tax-evasion amount* 50/50, they split the *joint surplus* 50/50. This is because the tax-evasion amount is denominated in money, and the joint surplus is denominated in utility.

5.2 Estimation Strategy

For each trader i, official j, time k, and shipment l, our three outcomes of interest are the relationship quality between the official and the trader q_{ijkl} (which is a question in our questionnaire that asks yes/no whether the trader has an especially friendly relationship with the official), the expected value of a bribe conditional on a bribe changing hands $E[b|b \neq 0]_{ijkl}$, and the tax paid t_{ijkl}.[24] Let m_{ijkl} be the number of times in the past that the official and the trader have been matched by random assignment. Let r_{jk} be an indicator for whether the official is a reviseur (versus a liquidateur). Let λ_i and λ_k be trader and time fixed effects. Let U_{jk} be a vector of official-level controls (e.g., age, gender, and rank). Let V_{ijkl} be a vector of shipment-level controls (e.g., tax owed) that our balance regression in Table A1 says are, despite random assignment, predictive of demographic characteristics. (Note that tax owed is not such a variable, but we include it anyway in our vector of controls out of an abundance of caution.[25])

With these variable definitions, our regression specification is as follows, with the β_{m1}s and β_{m2}s as our coefficients of interest, referring to the match effect on the liquidatuers and reviseurs respectively.

$$
\begin{aligned}
q_{ijkl} &= \alpha^q + \beta^q_{m1} m_{ijkl} + \beta^q_{m2}(m_{ijkl} \times r_{jk}) + \zeta^q r_{jk} + \gamma^q U_{jk} + \delta^q V_{ijkl} + \lambda^q_i + \lambda^q_k + \epsilon^q_{ijkl} \\
ln(b_{ijkl}) &= \alpha^b + \beta^b_{m1} m_{ijkl} + \beta^b_{m2}(m_{ijkl} \times r_{jk}) + \zeta^b r_{jk} + \gamma^b U_{jk} + \delta^b V_{ijkl} + \lambda^b_i + \lambda^b_k + \epsilon^b_{ijkl} \\
ln(t_{ijkl}) &= \alpha^t + \beta^t_{m1} m_{ijkl} + \beta^t_{m2}(m_{ijkl} \times r_{jk}) + \zeta^t r_{jk} + \gamma^t U_{jk} + \delta^t V_{ijkl} + \lambda^t_i + \lambda^t_k + \epsilon^t_{ijkl}
\end{aligned}
$$

We use logs because our model says that bribes and taxes are nonlinear in matches,[26] and logs are the easiest functional form to interpret: one match increases or decreases the outcome by β percent.

We have addressed a number of issues to ensure that this model is well-identified. First, if matches were endogenous (if, say, officials and traders could select into working together), then we would not know if the βs were the true effects or suffering from omitted variable bias. Luckily, our natural experiment means that matches are randomly assigned. Second, there is the possibility of noncompliance with random assignment. We therefore show the intention-to-treat (ITT) specifications in which our main regressor is the number of matches with the randomly assigned official, whether or not the trader actually ended up working with them. The first stage is very strong,[27] so the results do not change much between the ITT and the treatment-on-the-treated (TOT) specifications.[28][29] Third, there

[24] See Table A5 for the probability of a bribe as an additional outcome.

[25] Our results are not robust to including *log* tax owed in our vector of controls, which we interpret as benign; it tells us merely that the "true" structural relationship is one in which matches change the percent of taxes paid, not the percent of the share of taxes owed paid. See Table A6.

[26] Taking second-order conditions yields $\frac{\partial^2 t^*}{\partial m^2} \neq 0$ and $\frac{\partial^2 b^*}{\partial m^2} \neq 0$.

[27] See Table A7 for FS specifications.

[28] See Table A8 for TOT specifications

[29] In Q1-Q2 2021 we can observe the number of matches with the randomly assigned official ("Matches Original"), whereas beforehand we can only observe the number of matches with the official with whom the trader actually ended up working ("Matches Terminal"). Hence, our I.V. specifications use a subset of our data, while our non-I.V. specifications (see Table A9) use all of our data but make a conditional independence assumption.

is also the possibility that the random assignment has been corrupted (as would be the case if, say, the computer code had been compromised). Chalendard et al. (2021) do in fact have evidence of this happening at a port in Madagascar, so we have taken this concern seriously. However, we are reassured that this is not the case for three reasons: Tunisia has much higher state capacity than Madagascar; our conversations with "reformed" former customs officials and the traders in our sample, who are very forthcoming about corruption in general, say this does not happen; and our balance regressions in Table A2 show that few characteristics are predictive of the number of matches.

Fourth, under the best of circumstances, random assignment is not enough to identify the βs: officials and traders with more matches *overall*, because they have worked at the port longer or are more productive and manage more shipments, will mechanically have more matches with each other. This is why we control for trader fixed effects and inspector characteristics, including tenure.[30][31] Fifth, the Law of Large Numbers says that in the limit traders should end up working with all officials the same number of times. We therefore estimate our effects using random sampling variation within each trader's relatively small sample of matches. The Ministry of Finance cycles customs inspectors between ports every 2-3 years, such that each clearing agent has a relatively short history with each customs official, and hence the median number of matches is 13.

Overall, this is a very conservative specification that leaves little room for selection on unobservables.

5.3 Results

Figures 12-13 and Table 5 show the results of these econometric tests of the implications of our game theory model.

Testable Implication 1.1 says that as the match history goes up, trust goes up as well. Table 5 Column 1 shows the regression above taking relations as the outcome. (Recall that the outcome is the answer to a question in our questionnaire that asks yes/no whether the trader has an especially friendly relationship with the official.) Each additional match increases the probability that the trader describes the relationship positively by almost 1%. This result is consistent with our model-based hypothesis.

Testable Implication 1.2 says that as matches go up, trust goes up, and risk goes down; consequently, taxes paid go down. Figure 13 is a bin scatter plot that visualizes the raw relationship (without controls) between matches and taxes paid for liquidateurs, and we can see a clear negative relationship. More formally, Table 5 Column 3 shows our main regression with taxes paid as the outcome. Each additional match for the liquidateur lowers taxes paid (which is mechanically negatively correlated with tax evasion) by almost 1%. This result is consistent with our model-driven hypothesis.

Testable Implication 1.3 says that, even amidst matches increasing tax evasion, the effect on bribes is ambiguous and depends on the rate of change of the relative risk between officials and traders. Hence the specific parameter values we estimate will determine which version of our hypothesis is consistent with the data. As a start, Figure 12 is a bin scatter

[30] See Table A10 for specifications with alternative controls.

[31] We do not have the data for official fixed effects.

plot that visualizes the raw relationship (without controls) between matches and bribe amount for liquidateurs, and we can see a clear negative relationship. More formally, Table 5 Column 2 shows our main regression with taxes paid as an outcome. Each additional match for the liquidateur lowers bribes by approximately 1% and is strongly statistically significant. Interestingly, the effect is different for the different types of officials. While for liquidateurs the coefficient is -0.8%, for reviseurs the coefficient is +1%. Intuitively, this means that, relative to the risk to the trader, the risk to the liquidateur is decreasing *slower* but the risk to the reviseur is decreasing *faster*. (See Section 5.1.3 for more discussion on the intuition.)

Finally, we can test for heterogeneity to further explore mechanisms. Table 6 takes our main regression specification of bribes on matches and controls but interacts matches with an indicator for whether the goods were assigned to the red lane. Either result would be consistent with our model, depending on whether the match effect is complementary to or substitutable with the overall riskiness of the environment. On the one hand, if being in the red lane weakens the match effect, then we could conclude that matches matter less in an environment where the procedures guarantee a certain high degree of risk. On the other hand, if being in the red lane strengthens the match effect, then we could conclude that matches are especially important in a risky environment. We can see that being in the red lane weakens the match effect for liquidateurs, consistent with the first of these two competing hypotheses.

6 Macroeconomic Implications

6.1 Calculations

Our objective is to estimate bribery's fiscal cost by comparing the amount of revenue the government currently collects to the amount it would collect in a counterfactual scenario without bribery.[32]

We know that taxes collected today are just the number of shipments, times the taxes owed per shipment, times the share of taxes paid (i.e., the share of taxes *not* evaded).[33] Taxes collected under the counterfactual scenario are more complicated. The off-equilibrium approach says that the change is driven entirely by the share of taxes paid going up to 100%. But this does not account for a demand response. So the on-equilibrium approach says both that the share of taxes paid goes up to 100% *and* that traders change their behavior as a result of facing higher taxes. By not including a demand response, the off-equilibrium numbers are an overestimate of bribery's fiscal cost.

The traders' behavior change from facing higher taxes is governed by an import-demand elasticity ϵ, which is similar to the negative slope of a demand curve in any consumer-theory context. It determines the percent change in trade volume for every percent change

[32]Note that our calculations focus on trade-tax revenues, not on other tax revenues or government expenditures potentially impacted by general-equilibrium effects.

[33]We also know that taxes collected today are the GDP, times the tax-to-GDP ratio, times the trade-taxes-to-total-taxes ratio, which we know from OECD and World Bank data (OECD et al., 2020; World Bank, 2021). In practice, we use this alternative calculation because our measure of taxes owed per shipment is noisy.

in trade cost. In our context, we know the trade cost, which is just the change in taxes, bribes, and other fees observed in our data. Hence all we need to estimate the change in trade volume is calibrated estimates of ϵ from the trade literature.

Let t be the tax revenue per shipment. Let $T(b)$ be the government's total tax revenue. Let $S(b)$ be the share of taxes paid (i.e., the share of taxes *not* evaded). Let $V(b)$ be the trade volume in shipments. Let $C(b)$ be the trade cost per shipment. Let $T(b)$, $S(b)$, $V(b)$, and $C(b)$ all be functions of either the bribery equilibrium $b \neq 0$ or the no-bribery equilibrium $b = 0$. Let ϵ be the import-demand elasticity. Let Y be Tunisia's GDP, and let L be Tunisia's population.

With these variable definitions, our calculation specification is as follows.

$$\begin{aligned}
\underbrace{T(b \neq 0)}_{\text{Factual}} &= t \times S(b \neq 0) \times V(b \neq 0) \\
\underbrace{T(b = 0)}_{\text{Counterfactual}} &= t \times S(b \neq 0)[1 + \%\Delta S] \times V(b \neq 0)[1 + \%\Delta V] \\
&= t \times S(b \neq 0)[1 + \%\Delta S] \times V(b \neq 0)[1 + (\epsilon \times \%\Delta C)] \\
\Rightarrow \text{Anti-Corruption Dividend (\% GDP)} &= \frac{T(b = 0) - T(b > 0)}{Y} \\
\Rightarrow \text{Anti-Corruption Dividend (\$ } \textit{Per Capita}) &= \frac{T(b = 0) - T(b > 0)}{L}
\end{aligned}$$

Importantly, these calculations are only focused on fiscal cost. Bribery likely has many other economic costs, such as generating uncertainty, disrupting price signals, and rewarding risk-tolerant, politically connected, or antisocial firms over potentially more productive ones. In addition, as the political-science literature cited above shows, bribery can also erode democratic legitimacy. In other words, while we argue that not accounting for bribery's potential trade effects leaves us with an overestimate of its fiscal cost, the fiscal cost itself is likely an underestimate of the total cost.

6.2 Results

Using our methodology, we can calculate the tax revenue effects of bribery as a function of the import-demand elasticity. We report our results in Table 7 and Figure 14 (which has a Laffer curve interpretation). We report the tax-revenue effects as a percent of GDP and in *per capita* terms. We also report our effects assuming different elasticities, with various numbers from the trade literature. Our preferred estimate, -1.75, is approximately the midpoint of the studies of which we are aware that estimate a trade elasticity for Tunisia specifically (Kee et al., 2008; Tokarick, 2010).

Note that our trade elasticity is less than some numbers cited in the trade literature because it measures the response to a *highly aggregated* change in trade costs. Some trade elasticities measure the response of the trade in one good to a change in the price of another good, similar to a cross-price elasticity in consumer theory; our trade elasticity measures the response of the trade in an average good to a change in the average effective tax rate.

Necessarily, the latter is lower than the former, since it is less affected by between-good substitution.

Overall, Table 7 shows that bribery's fiscal costs are meaningfully large. Our preferred estimate is that an annual anti-corruption dividend could send every Tunisian citizen an $80 check or allow the Tunisian government to spend an additional 0.7% of GDP on education, health, security, or any other valuable use. $80 is enough to provide bread (the staple food for low-income Tunisians) to a family of four for nine months, and 0.7% of GDP is the approximate cost of the economic damage from climate change in the United States (Hsiang et al., 2017).

7 Conclusion

We overcome the data and identification challenges inherent to investigating bribery: we build an original dataset on Tunisian customs transactions using an audit study to directly observe bribes, and we leverage a natural experiment in which a computer algorithm randomly assigns customs officials to import shipments. There are three sets of results. First, we show that bribery and tax evasion are widespread, that bribery is collusive (not coercive), and that age (but not gender) predicts officials' corruptibility. Second, in line with a straightforward Nash bargaining model, we show that the length of official/trader relationships increases tax evasion but decreases bribe amounts. Third, we zoom out to consider the larger macroeconomic implications and show that, in terms of lost tax revenue, bribery costs the Tunisian government 0.7% of GDP or $80 per citizen.

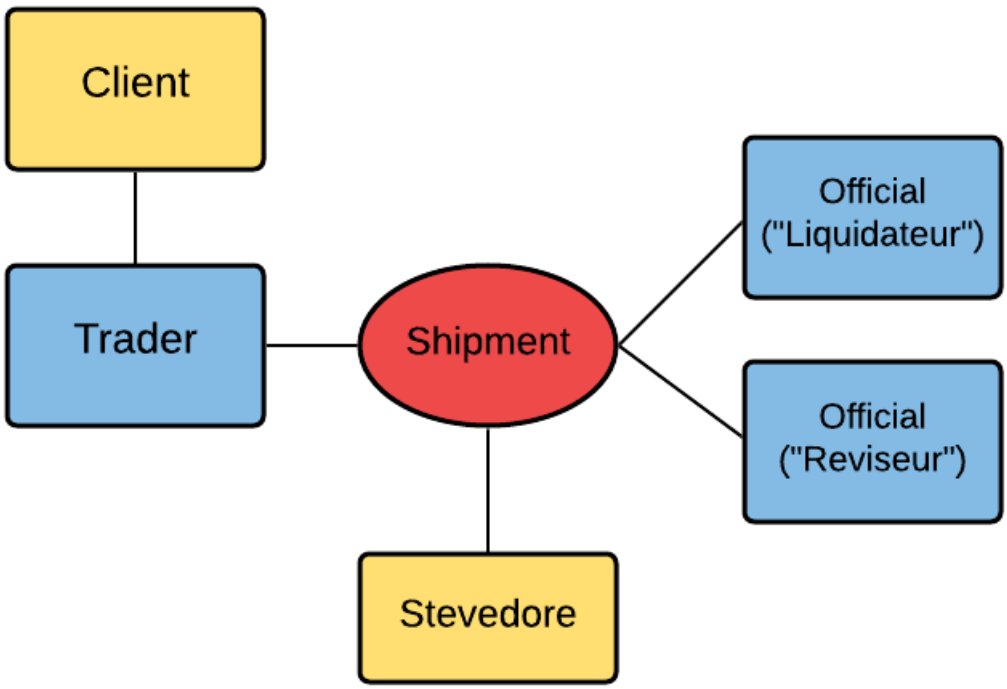
There are many opportunities for future work building off of these findings. First, audit studies are a useful (if difficult) way of collecting data on bribery, so researchers could continue to use this methodology in a wide variety of settings. Second, researchers could test our model, or an even richer version of it, to see if it is useful in general for explaining corruption dynamics. Third, given the difficulty in observing bribery and tax evasion in customs transactions, researchers could investigate whether firms have well-anchored beliefs about the costs of participating in international trade.

Our findings also have important and interesting policy implications. First, there could (depending on the details) be greater anti-corruption returns to hiring younger officials than to hiring female officials - though there are of course many other reasons to work toward gender parity in the Tunisian administration. Second, there is merit to the "regulatory capture" fear that motivates officials being randomly assigned to and frequently rotated around different postings. Governments could further their fight against corruption by recommitting to these policies and finding other ways to better monitor officials and traders known to have a high number of repeated interactions (or a high score on some other proxy for trustworthy relationships). Third, bribery and tax evasion are hugely consequential to the Tunisian government and economy and could therefore be worth prioritizing.

Overall, knowing that dynamics matter for corruption can help reform-minded governments decide which levers to pull as they work to enhance transparency. The large economic cost of trade corruption implies a high return on investment for the governments that succeed.

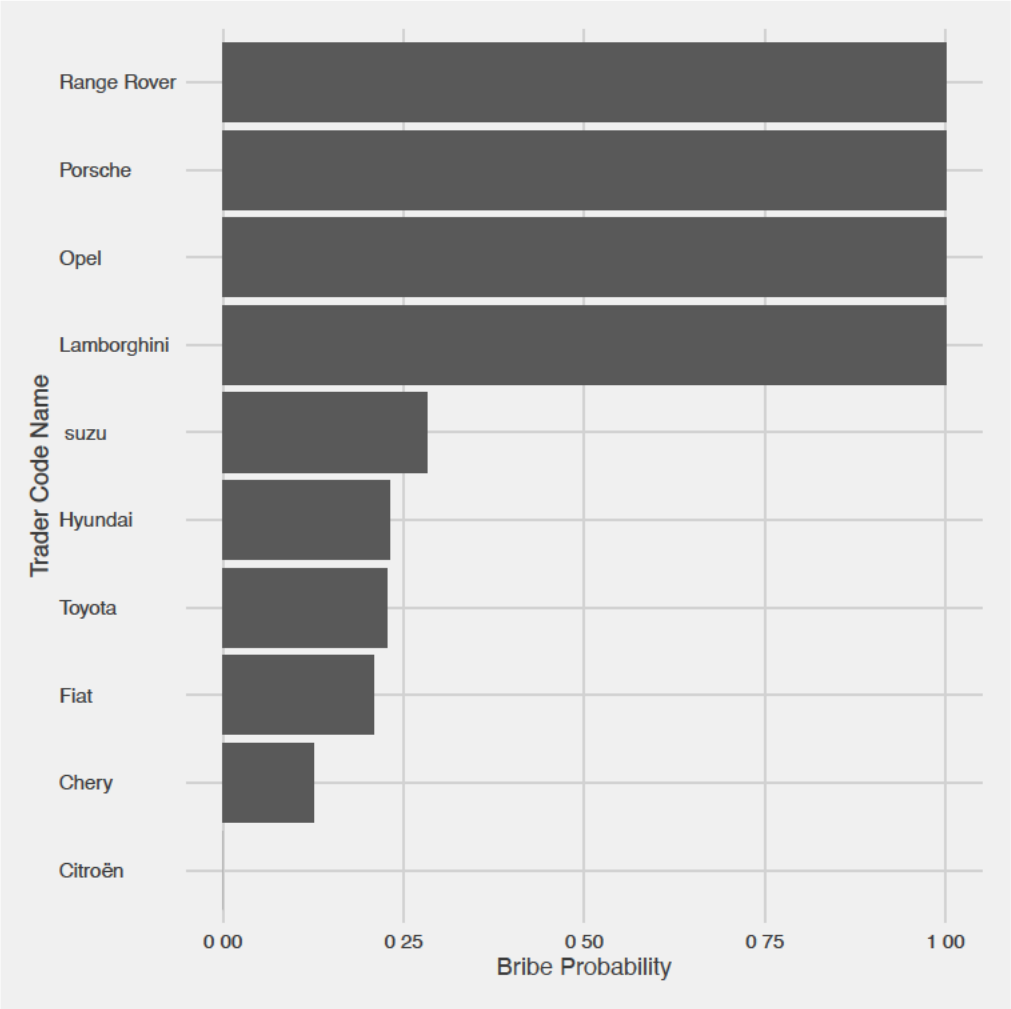
Figures

Figure 1
Actors Involved in Tunisian Customs Transactions



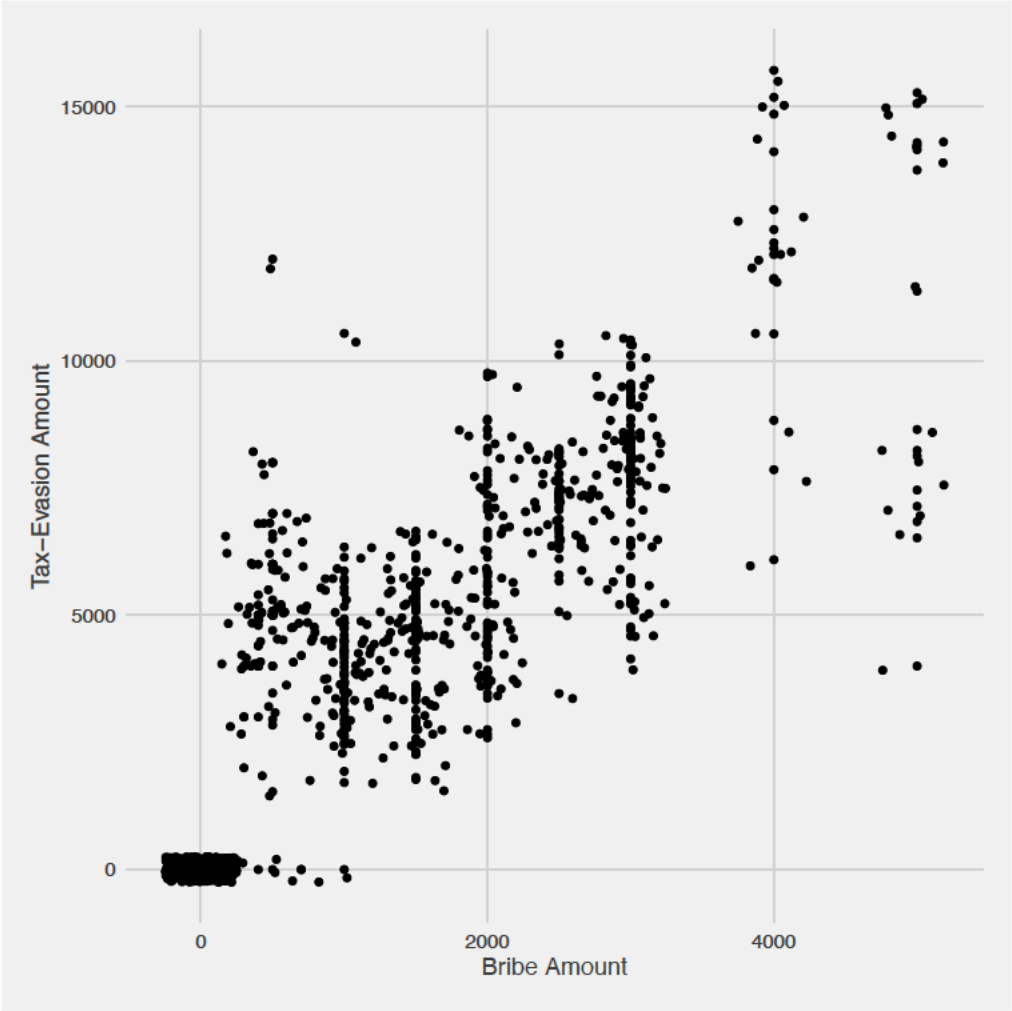
Note:
The figure visualizes the actors involved in Tunisian customs transactions, in relation to each import shipment and to each other. Actors who feature prominently in our study are in blue. Other actors are in yellow.

Figure 2
Traders' Willingness to Reveal Paying Bribes



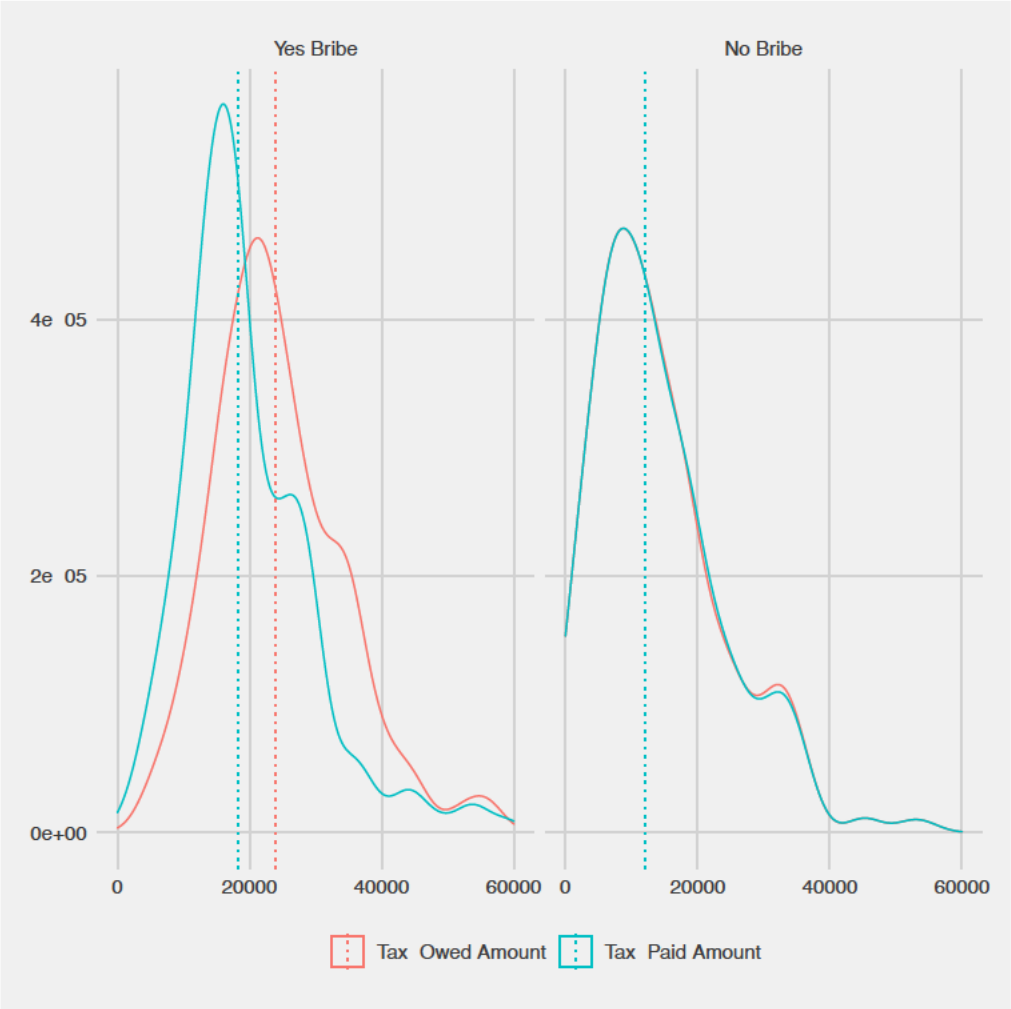
Note:
The figure is a bar chart visualizing the proportion of surveys for which each trader revealed paying bribes, where traders are identified by their code names. The sample used is all data from the latest (2021) version of our survey, for which these ten traders contributed the vast majority of the surveys (90%).

Figure 3
Tax Evasion as Function of Bribery



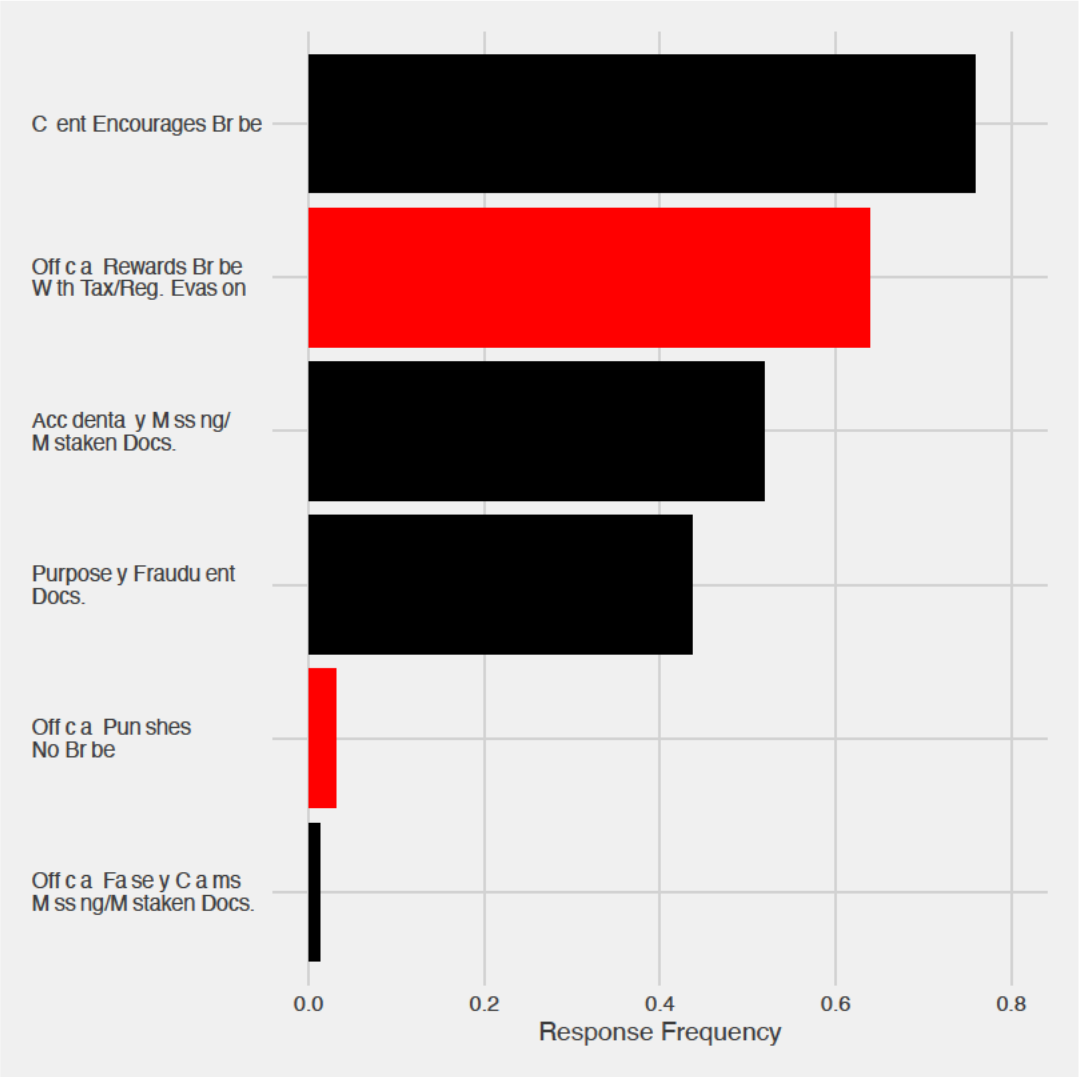
Note:
The figure is a scatter chart visualizing tax evasion as a function of bribery. The x-axis represents the bribe amount paid by the trader to the liquidateur official. The y-axis represents the tax-evasion amount, defined as the tax owed less the tax paid. Monetary values are in USD. The figure plots data jittered by up to $250 in each direction and is trimmed at the top/bottom 1%. The sample used is all data from the latest (2021) version of our survey.

Figure 4
Taxes Owed and Taxes Paid by Bribery



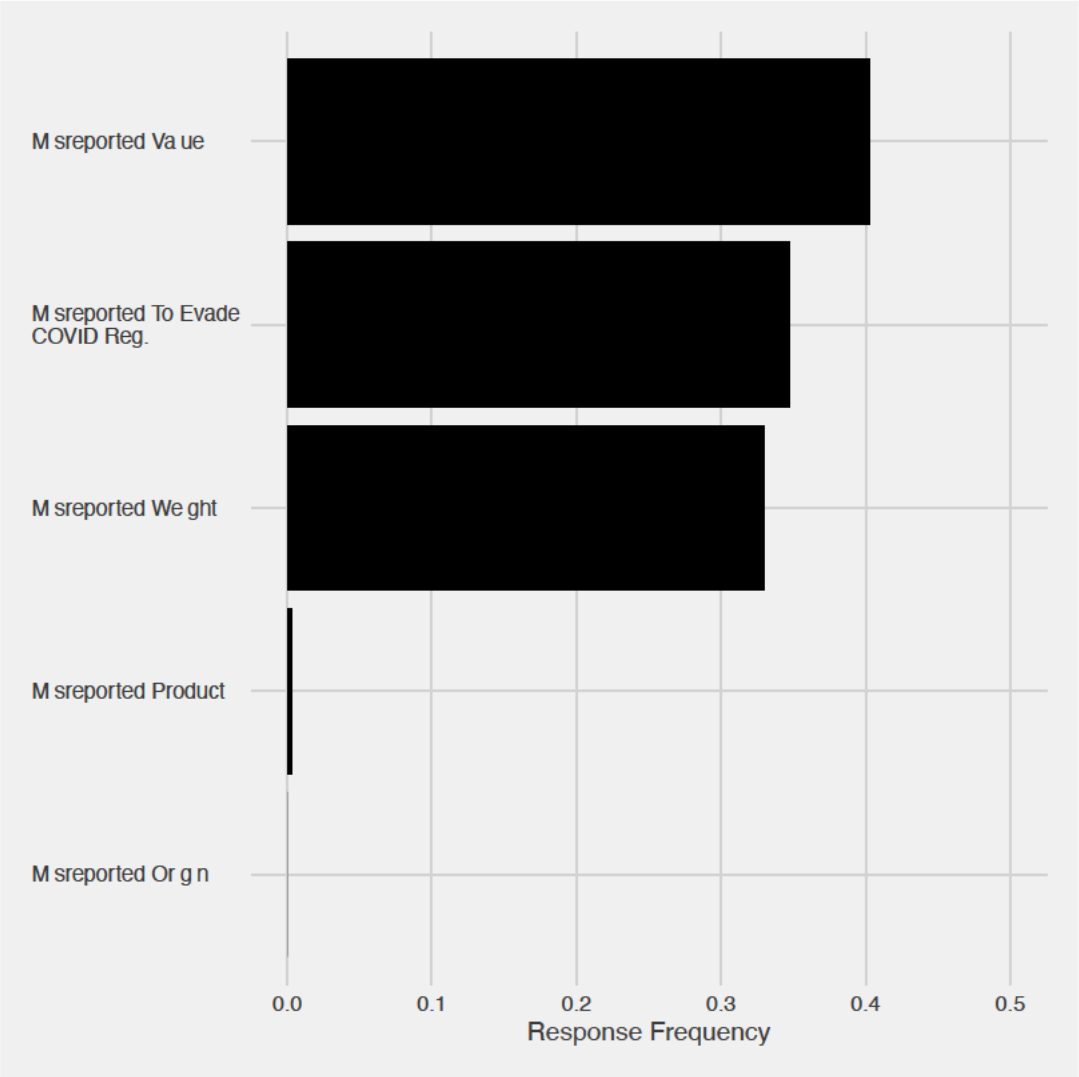
Note:
The figure is a kernel-density chart visualizing taxes owed and taxes paid broken down by whether a bribe changed hands or not. The figure uses the kernel-density algorithm to plot nonparametric estimates of the probability density functions. In the left-hand panel, the two lines represent taxes owed and taxes paid for transactions in which the trader did not pay a bribe. In the right-hand panel, the two lines represent taxes owed and taxes paid for transactions in which the trader paid a bribe. Monetary values are in USD. The respective medians are represented by a dotted vertical line. Monetary values are in USD. The sample used is all data from the latest (2021) version of our survey.

Figure 5
Why Traders Pay Bribes



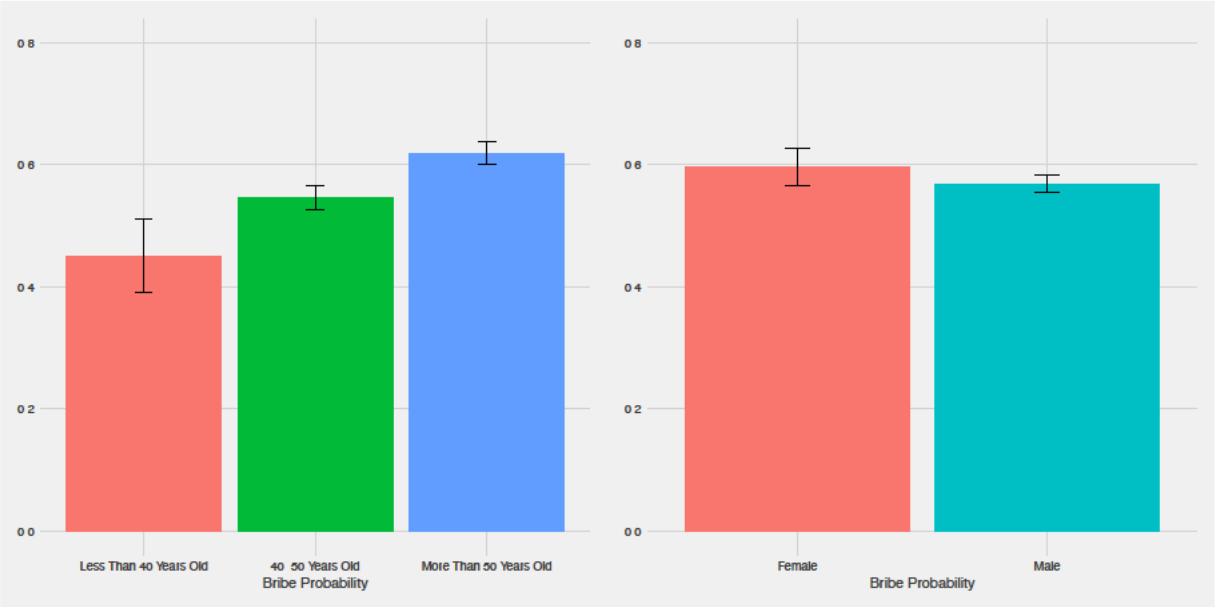
Note:
The figure is a bar chart visualizing how traders respond when asked why they paid a bribe. The y-axis represents the responses, which were answers to a multiple-choice question to which the traders could select all that applied. The x-axis represents the frequency with which each answer was selected. The two red bars highlight the cases with clear collusion and clear coercion. The sample used is all data from the latest (2021) version of our survey.

Figure 6
How Traders Evade Taxes



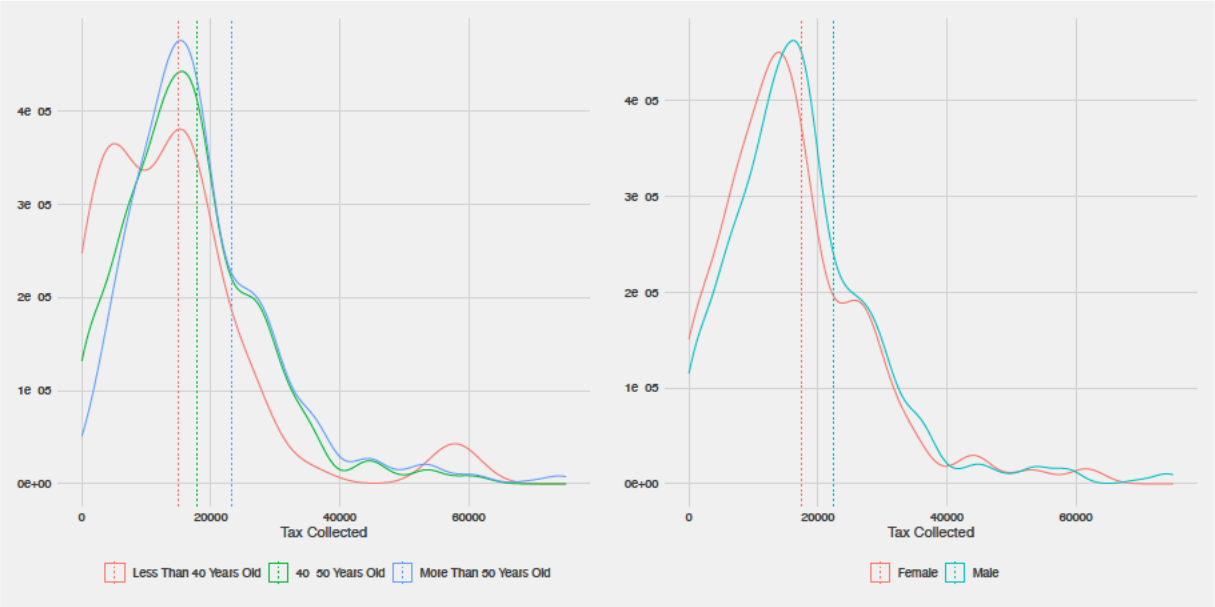
Note:
The figure is a bar chart visualizing how traders respond when asked how they evade taxes. The y-axis represents the responses, which were answers to a multiple-choice question to which the traders could select all that applied. The x-axis represents the relative frequency with which each answer was selected. The sample used is all data from the latest (2021) version of our survey.

Figure 7
Bribe Probability by Officials' Demographics



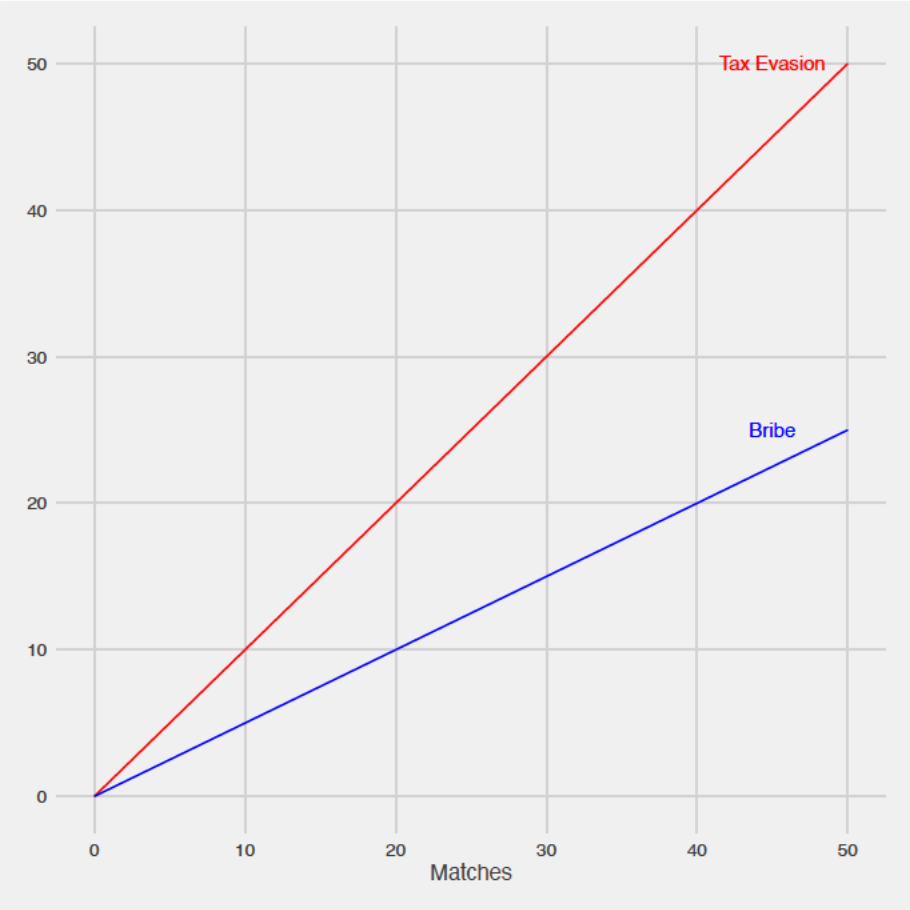
Note:
The figure is two bar charts visualizing bribe probability broken down by officials' demographics. In the left-hand panel, the three bars represent official age. In the right-hand panel, the two bars represent official gender. The y-axis represents bribe probability. Standard-error-bars cover the mean plus/minus two standard deviations. The sample used is all data from the latest (2021) version of our survey.

Figure 8
Tax Collected by Officials' Demographics



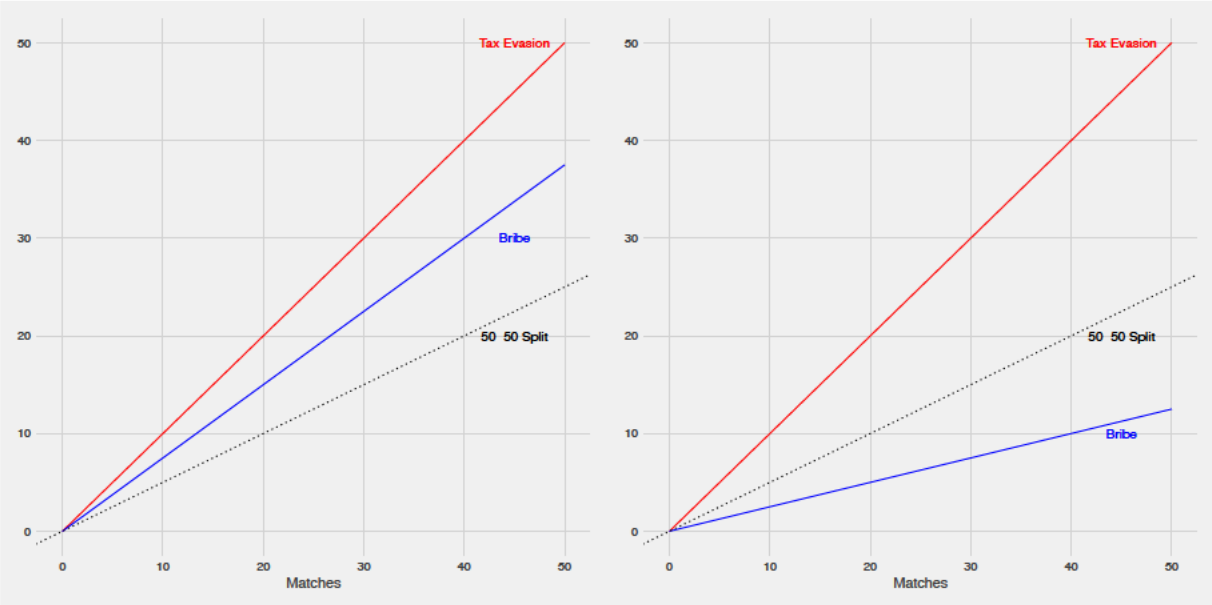
Note:
The figure is two kernel-density charts visualizing tax collected broken down by officials' demographics. The figure uses the kernel-density algorithm to plot nonparametric estimates of the probability density functions. In the left-hand panel, the three lines represent official age. In the right-hand panel, the two lines represent official gender. Monetary values are in USD. The respective medians are represented by a dotted vertical line. The sample used is all data from the latest (2021) version of our survey.

Figure 9
Game Theory Model Parameterization with 50/50 Tax-Evasion Split



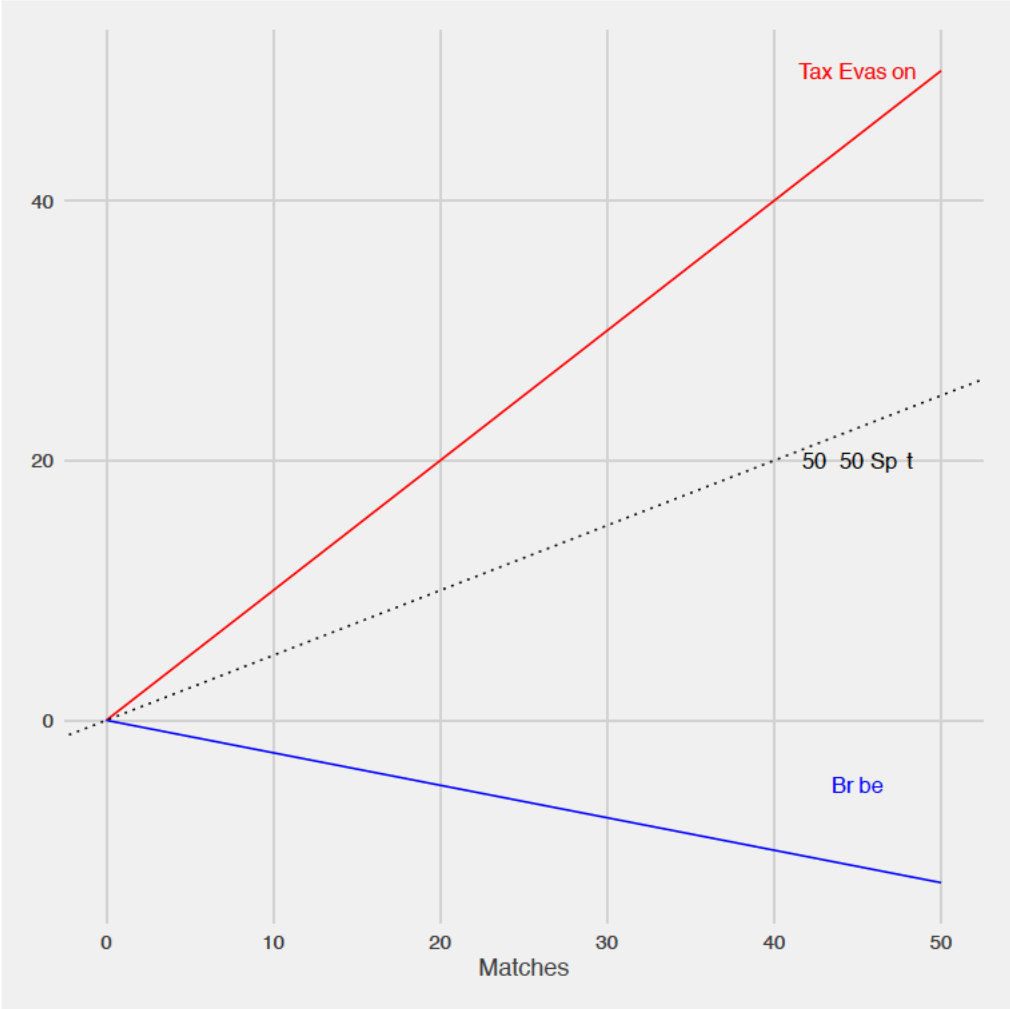
Note:
The figure is a simulation of our Nash bargaining model. The x-axis represents the number of matches between the trader and the official, measured from some baseline. The y-axis represents monetary amounts in excess of those at the baseline, where the red line is the tax-evasion amount and the blue line is the bribery amount. The paramterization is one with a 50/50 tax-evasion split. Mathematically: $\frac{\partial b^*}{\partial m} = \frac{1}{2}\frac{\partial(\tilde{t}-t^*)}{\partial m} = -\frac{1}{2}\frac{\partial t^*}{\partial m}$.

Figure 10
Game Theory Model Parameterization with Uneven Tax-Evasion Split



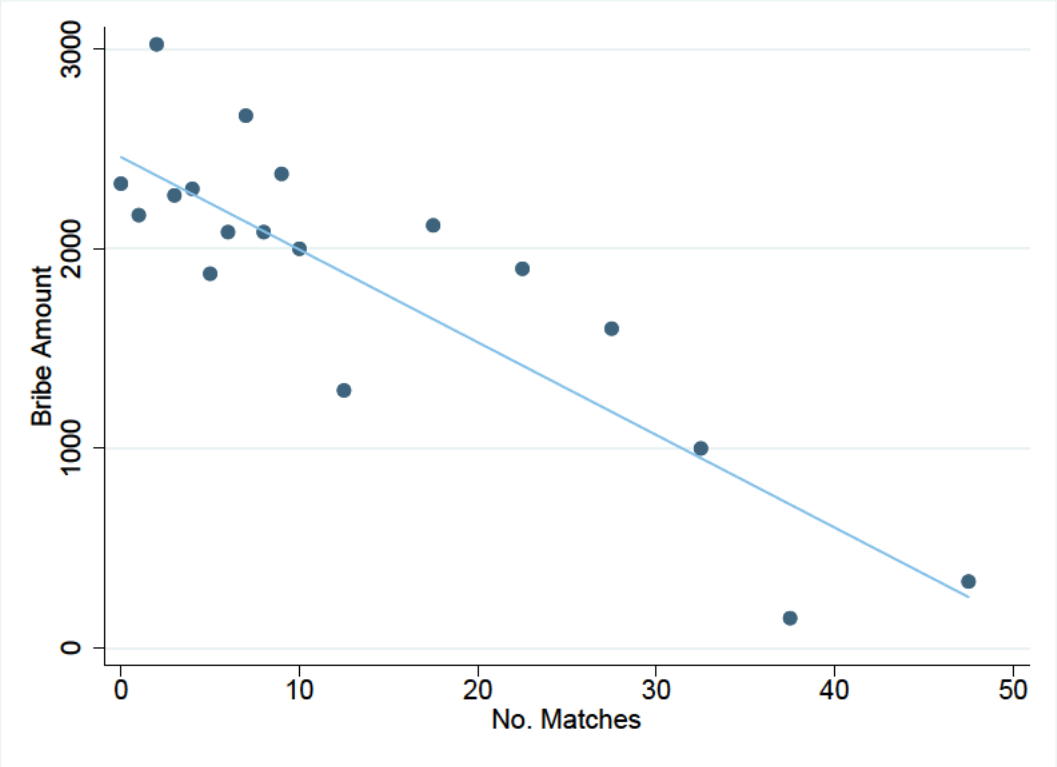
Note:
The figure is a simulation of our Nash bargaining model. The x-axis represents the number of matches between the trader and the official, measured from some baseline. The y-axis represents monetary amounts in excess of those at the baseline, where the red line is the tax-evasion amount and the blue line is the bribery amount. The black dotted line represents a 50/50 split of the tax-evasion amount between the trader and the official (whose share is the bribe). In the plot on the left, the blue line is above the black line. This parameterization is one for which matches increase the official's share of the pie. In the plot on the right, the blue line is below the black line. This parameterization is one for which matches decrease the official's share of the bribe. Mathematically: $\frac{\partial b^*}{\partial m} \neq \frac{1}{2}\frac{\partial(\bar{t}-t^*)}{\partial m} = -\frac{1}{2}\frac{\partial t^*}{\partial m}$.

Figure 11
Game Theory Model Parameterization with Bribery/Tax-Evasion Divergence



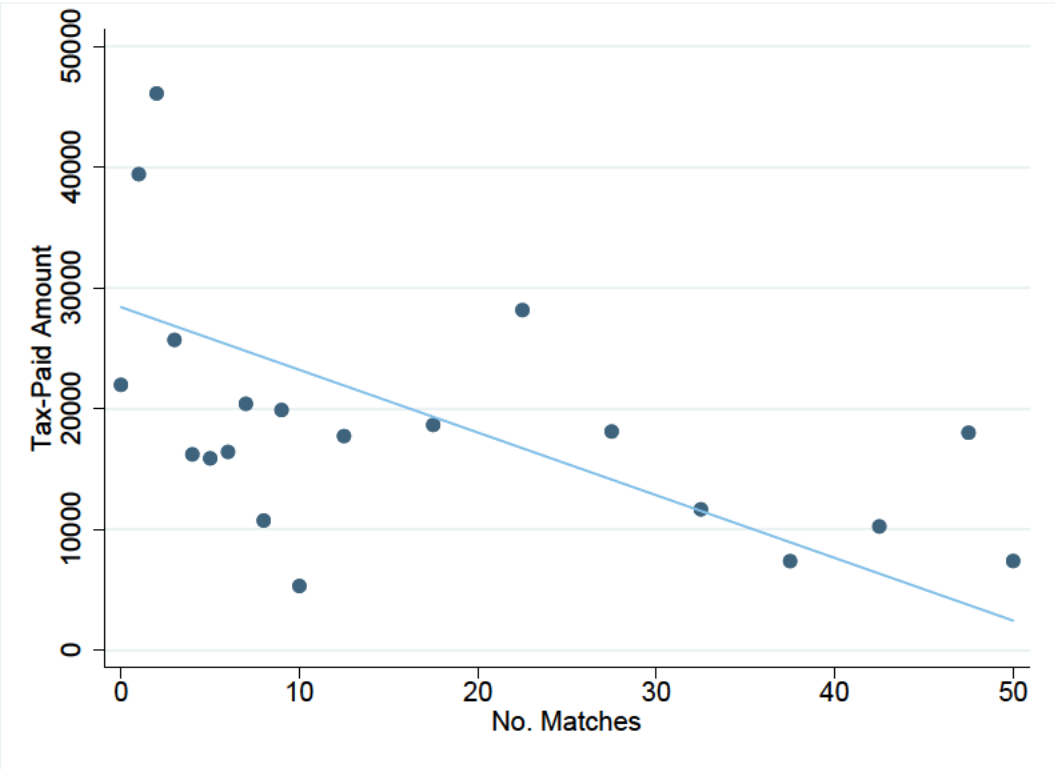
Note:
The figure is a simulation of our Nash bargaining model. The x-axis represents the number of matches between the trader and the official, measured from some baseline. The y-axis represents monetary amounts in excess of those at the baseline, where the red line is the tax-evasion amount and the blue line is the bribery amount. The black dotted line represents a 50/50 split of the tax-evasion amount between the trader and the official (whose share is the bribe). Since the blue line is below the x-axis, this parameterization is one for which matches decrease the official's share of the bribe so much that, even though the pie gets bigger, her amount of the pie gets smaller. Mathematically: $\frac{\partial b^*}{\partial m} < 0$, $\frac{\partial(\tilde{t}-t^*)}{\partial m} > 0$ & $\frac{\partial t^*}{\partial m} < 0$.

Figure 12
Effect of No. Matches on Bribery



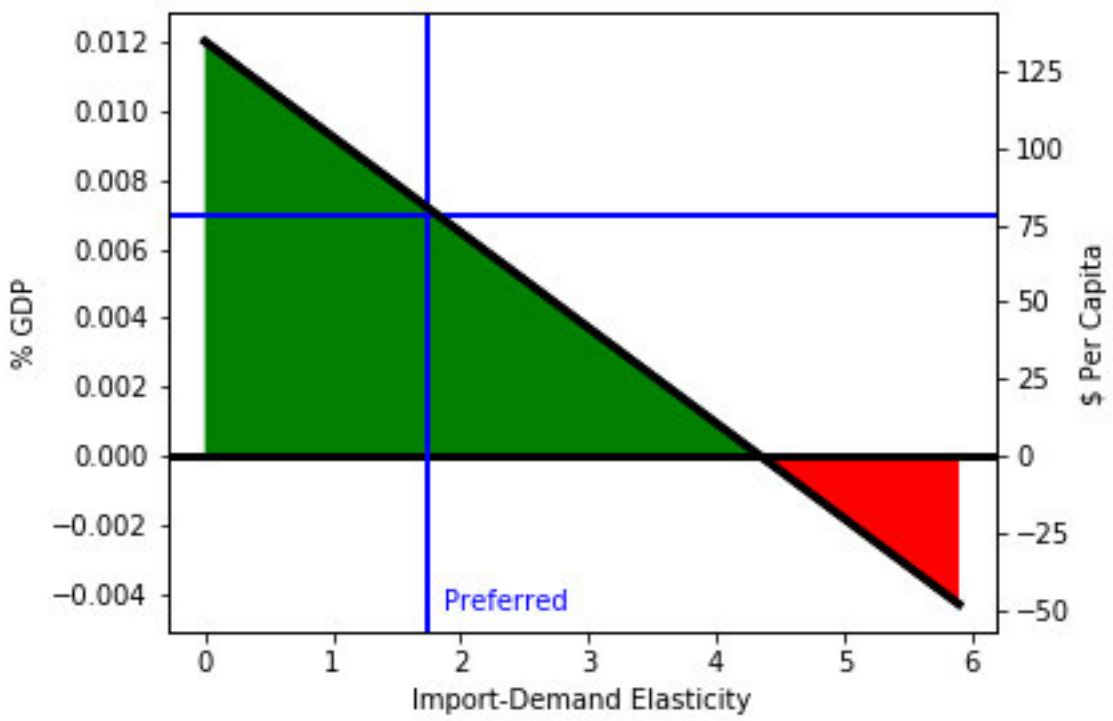
Note:
The figure is a binscatter chart visualizing the effect of the number of matches on bribery. The x-axis represents the number of matches between the trader and the official originally assigned to the trader. The y-axis represents the bribe amount. Monetary values are in USD. The figure sorts the data into equally sized bins and plots the average x and y values in each bin. The line is a line of best fit calculated using Stata's *binscatter* package. The sample used is all data from the latest (2021) version of our survey.

Figure 13
Effect of No. Matches on Tax Evasion



Note:
The figure is a binscatter chart visualizing the effect of the number of matches on tax evasion. The x-axis represents the number of matches between the trader and the official originally assigned to the trader. The y-axis represents the tax-paid amount. Monetary values are in USD. The figure sorts the data into equally sized bins and plots the average x and y values in each bin. The line is a line of best fit calculated using Stata's *binscatter* package. The sample used is all data from the latest (2021) version of our survey.

Figure 14
Anti-Corruption Dividend as Function of Import-Demand Elasticity



Note:
The figure visualizes the "anti-corruption dividend" as a function of the import-demand elasticity. The x-axis represents alternative assumed import-demand elasticities. The left-hand y-axis represents the added tax revenue from eradicating bribery, expressed as a percent of GDP. The right-hand y-axis represents the added tax revenue from eradicating bribery, expressed as U.S. dollars per citizen. The green area signifies positive fiscal returns to eradicating bribery. The red area signifies negative fiscal returns to eradicating bribery. The vertical blue line represents our preferred trade elasticity, which is -1.75 because it is the midpoint of all the studies of which we are aware that estimate a trade elasticity for Tunisia specifically. The horizontal blue line represents the added tax revenue corresponding to our preferred trade elasticity.

Tables

Table 1
Shipment and Official Descriptives

	Mean	Median	Min	Max	SD	N
Shipment KGs	72,163	7,525	1	45,000,000	1,617,590	774
Shipment Value	36,265	32,062	53	354,992	34,715	774
Tax Owed	8,853	7,027	4	90,000	9,405	774
Other Trade Costs	2,526	324	21	73,962	7,435	774
Red Lane	0.88	1	0	1	0.32	774
Client Shipments/Y	60	55	5	100	16.96	737
Client Employees	56	55	0	105	20.41	738
Age Official	49	45	35	65	6.03	1423
Female Official	0.18	0	0	1	0.38	1423

Note:
The table shows descriptive statistics on shipment and official variables. Observations are at the shipment-level, except for the official characteristics, which are at the official-level. Red Lane is defined as an indicator variable for whether the goods passed through the high-enforcement "red lane." Monetary values are in USD. The sample used is all data from the latest (2021) version of our survey.

Table 2
Bribery and Tax Descriptives

	Mean	Median	Min	Max	SD	N
Bribe Yes/No	0.57	1	0	1	0.49	1423
Bribe Amount	719	540	10.8	30,394	1,242	815
Tax Paid	7,651	5,762	3.6	90,000	8984.57	774
Tax Owed	8,853	7,027	3.6	90,000	9404.76	774
Owed - Paid	1,202	949	-2,045	14,400	1,553	774
1 - (Paid / Owed)	0.13	0.14	-0.5	0.8	0.14	774
Paid / Owed	0.87	0.86	0.20	1.50	0.14	774
Tax Rate	0.30	0.19	0	2.76	0.26	774
No. Matches	14	13	0	50	11.94	1423

Note:
The table shows descriptive statistics on bribery and tax variables. Observations are at the official-level, except for the taxes, which are at the shipment-level. Monetary values are in USD. The sample used is all data from the latest (2021) version of our survey.

Table 3
Proportion of Bribery and Tax Evasion "Regimes"

		Bribery		
		No	Yes	Total
Tax Evasion	No	42.45	4.08	46.52
	Yes	0.21	53.27	53.48
	Total	42.66	57.34	100.00

Note:
The table shows our results on the proportion of bribery and tax evasion "regimes." Observations are at the official-level. Tax Evasion is defined as Yes if Tax Owed > Tax Paid and No otherwise. The sample used is all data from the latest (2021) version of our survey.

Table 4
Effect of Officials' Demographics on Bribery and Tax Evasion

	(1) Bribe Yes/No	(2) Tax Paid (Log)
Age Official	0.016***	0.011***
	(0.002)	(0.003)
Female Official	0.007	0.011
	(0.027)	(0.045)
Outcome Mean	.57	9.52
Observations	1,358	1,358
Month-by-Year FE	YES	YES
Controls	YES	YES

Note:
The table shows our regression results for the effect of officials' demographics on bribery and tax evasion. Observations are at the official-level. In Column 1, the dependent variable is an indicator for whether a bribe was exchanged. In Column 2, the dependent variable is the log of the amount of tax paid. The independent variables of interest are official age and gender, coded as ten-year bins and a female indicator respectively. Monetary values are in USD. The regressions also have month-by-year fixed effects, official controls (rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, client employees, and client trade volume). In the parentheses are robust standard errors clustered at the shipment level. (*** p<0.01, ** p<0.05, * p<0.1.) The sample used is all data from the latest (2021) version of our survey.

Table 5
Effect of No. Matches on Bribery and Tax Evasion

	(1) Esp. Friendly Yes/No	(2) Bribe (Log)	(3) Tax Paid (Log)
No. Matches (Liquidateur)	0.009***	-0.008**	-0.008**
	(0.003)	(0.004)	(0.004)
No. Matches (Reviseur)	0.001	0.010**	0.001
	(0.002)	(0.004)	(0.003)
Outcome Mean	.33	7.15	9.52
Observations	1,358	769	1,358
R^2	0.504	0.794	0.755
Trader FE	YES	YES	YES
Month-by-Year FE	YES	YES	YES
Controls	YES	YES	YES

Note:
The table shows our regression results for the effect of the number of matches on bribery and tax evasion. Observations are at the official-level. In Column 1, the dependent variable is the relationship quality between the official and the trader (which is a question in our questionnaire that asks yes/no whether the trader has an especially friendly relationship with the official). In Column 2, the dependent variable is the log of the bribe amount, conditional on a bribe being exchanged. In Column 3, the dependent variable is the log of the amount of the tax paid. The independent variables of interest are the number of matches between the trader and the official originally assigned to the trader, for both the liquidateur and the reviseur. Monetary values are in USD. The regressions also have trader fixed effects, month-by-year fixed effects, official controls (age, gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, client employees, and client trade volume). In the parentheses are robust standard errors clustered at the shipment level. (*** p<0.01, ** p<0.05, * p<0.1.) The sample used is all data from the latest (2021) version of our survey.

Table 6
Heterogeneous Effects by Risk Environment

	Bribe (Log)
No. Matches (Liquidateur)	-0.037***
	(0.014)
No. Matches (Reviseur)	0.006
	(0.006)
No. Matches (Liquidateur)×Red Lane	0.029**
	(0.014)
No. Matches (Reviseur)×Red Lane	0.005
	(0.005)
Outcome Mean	7
Observations	769
R^2	0.794
Trader FE	YES
Month-by-Year FE	YES
Controls	YES

Note:
The table shows our regression results for the heterogeneous effects of the number of matches on bribery broken down by risk environment. The dependent variable is the log of the bribe amount, conditional on a bribe being exchanged. The independent variables of interest are the number of matches between the trader and the official originally assigned to the trader, for both the liquidateur and the reviseur, and their interactions with a red-lane indicator. Monetary values are in USD. The regressions also have trader fixed effects, month-by-year fixed effects, official controls (age, gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, client employees, and client trade volume). In the parentheses are robust standard errors clustered at the shipment level. (*** p<0.01, ** p<0.05, * p<0.1.) The sample used is all data from the latest (2021) version of our survey.

Table 7
Anti-Corruption Dividend as Function of Import-Demand Elasticity

Import-Demand Elasticity	-1.75 (Preferred)	0	-1	-2	-3	-4	-5
% GDP	0.7	1.2	0.9	0.6	0.4	0.1	-0.2
$ *Per Capita*	80	134	103	72	41	10	-21

Note:
The tables shows our results on the "anti-corruption dividend" as a function of the import-demand elasticity. The x-axis represents alternative assumed import-demand elasticities, with -1.75 being our preferred calibration because it is the midpoint of all the studies of which we are aware that estimate a trade elasticity for Tunisia specifically. The y-axis represents different ways of reporting the numbers, namely either as a percent of GDP or as U.S. dollars per citizen. The sample used is all data from the latest (2021) version of our survey.

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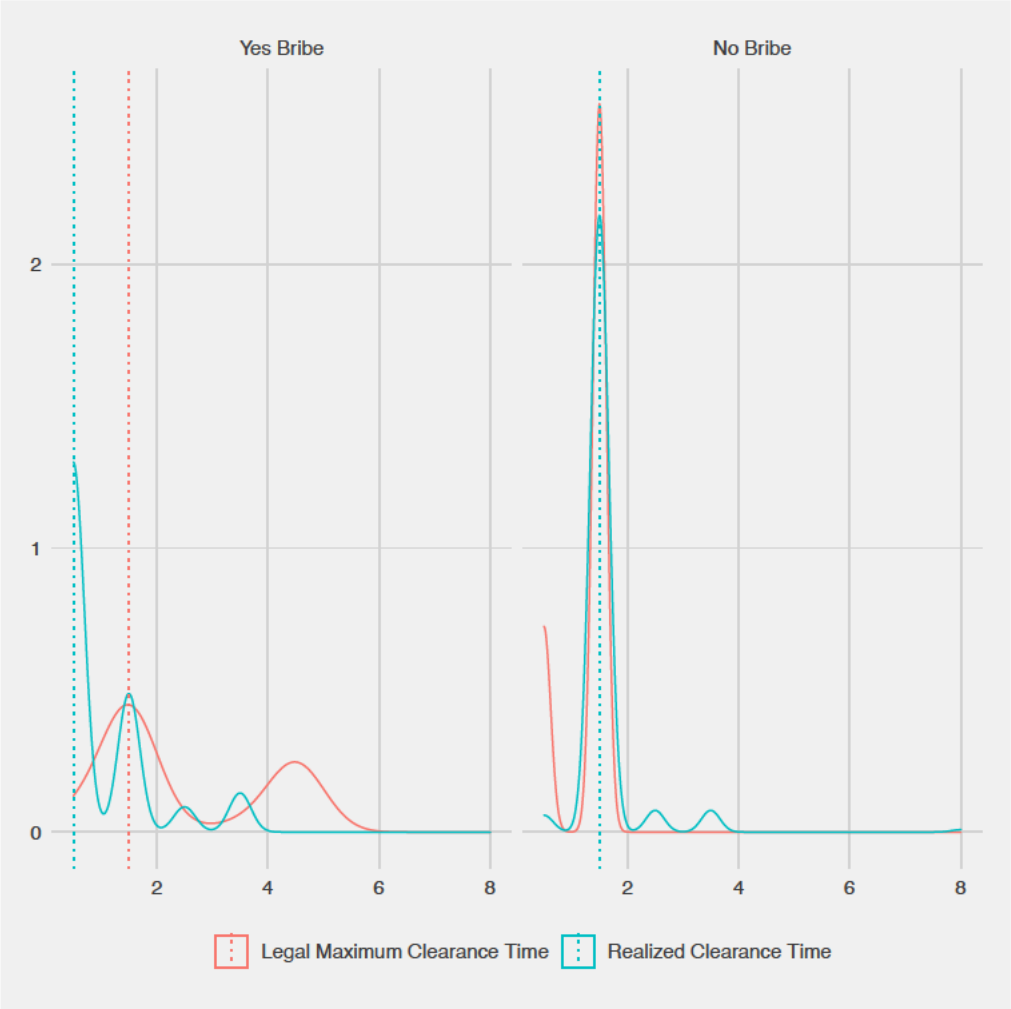
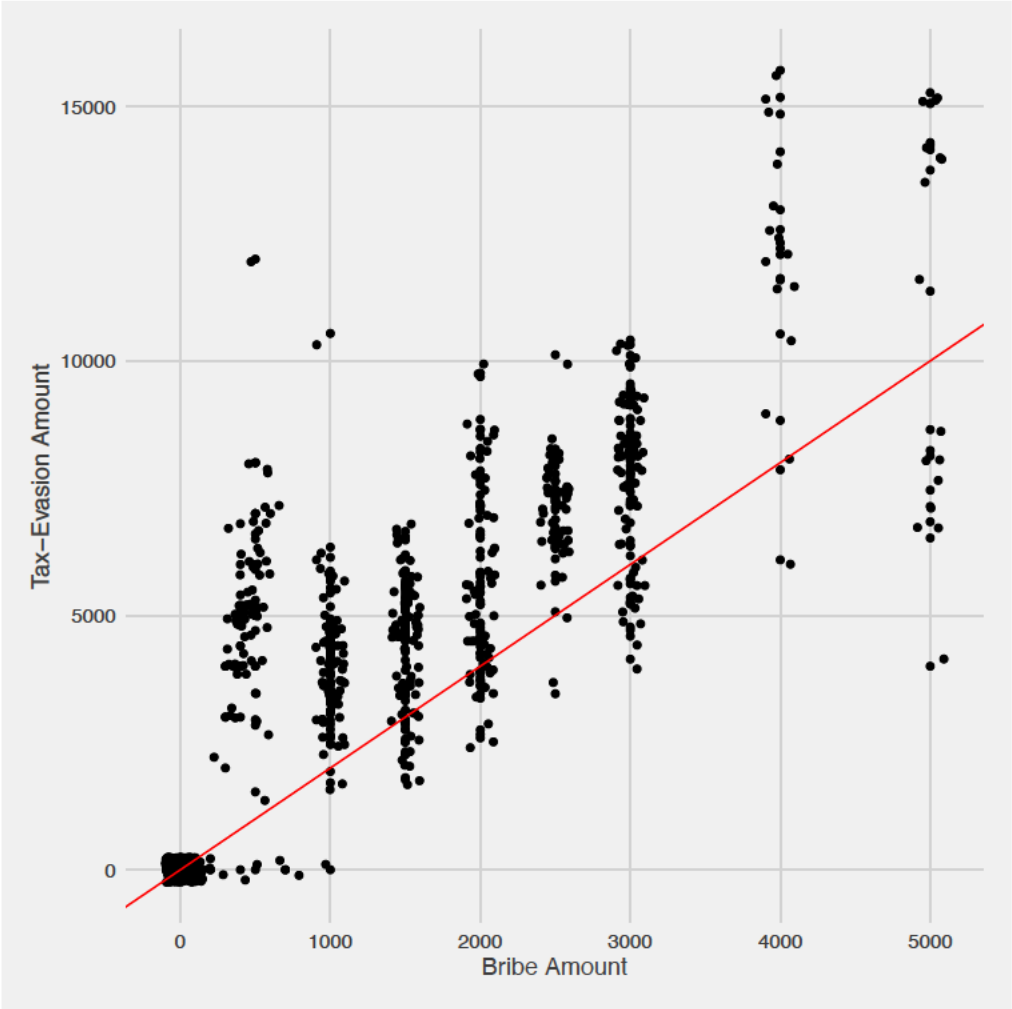
A Figures

Figure A1
Clearance Time by Bribery



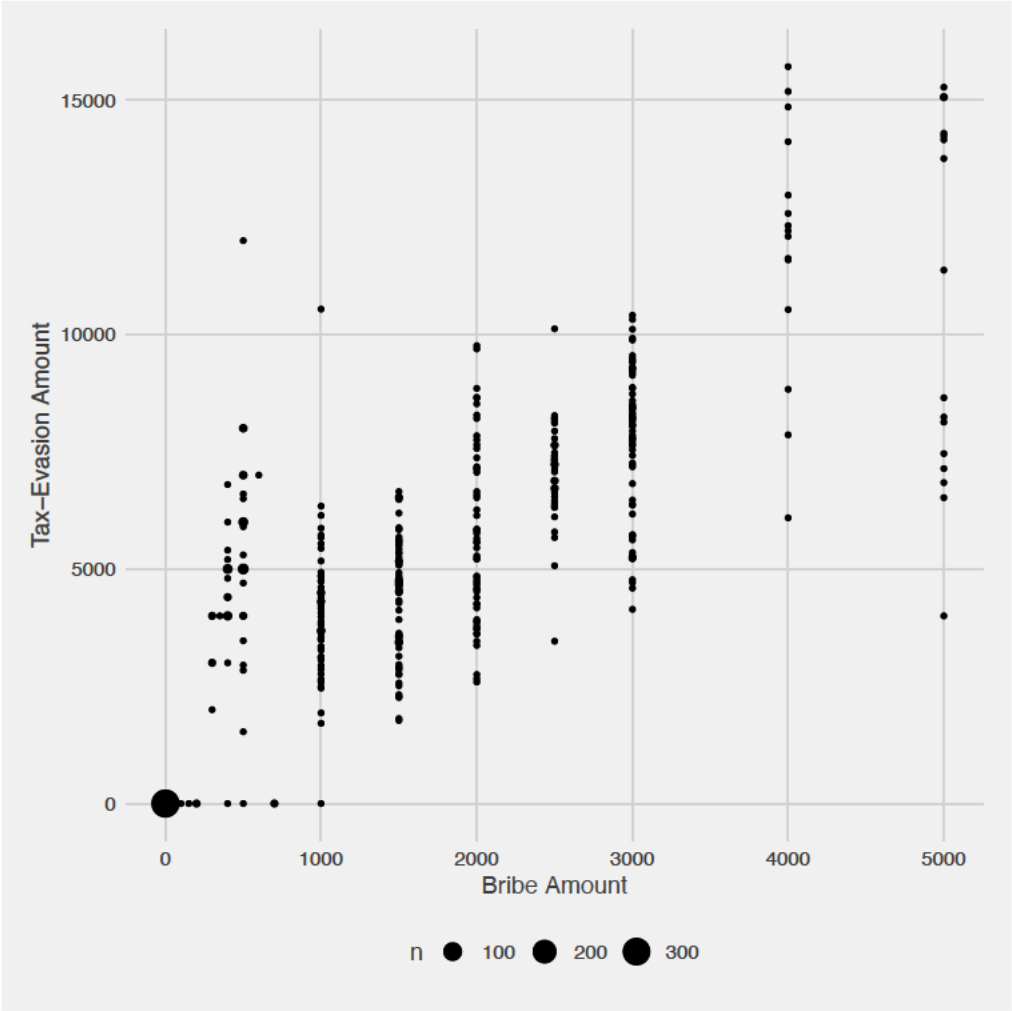
Note:
The figure is a kernel-density chart visualizing clearance time by bribery. The figure uses the kernel-density algorithm to plot nonparametric estimates of the probability density functions. In the left-hand panel, the two lines represent the legal maximum clearance time and the realized clearance time for transactions in which the trader paid a bribe. In the right-hand panel, the two lines represent the legal maximum clearance time and the realized clearance time for transactions in which the trader did not pay a bribe. Monetary values are in USD. The respective medians are represented by a dotted vertical line. The sample used is all data from the latest (2021) version of our survey.

Figure A2
Tax Evasion as Function of Bribery (Line of Best Fit)



Note:
The figure is a scatter chart visualizing tax evasion as a function of bribery. The x-axis represents the bribe amount paid by the trader to the liquidateur official. The y-axis represents the tax-evasion amount, defined as the tax owed less the tax paid. Monetary values are in USD. The figure plots data jittered by up to $250 in each direction and trimmed at the top/bottom 1%. The red line represents a 50/50 split of the tax-evasion amount between the official and the trader; data above the line means the trader has a larger share; data below the line means the official has a larger share. The sample used is all data from the latest (2021) version of our survey. The figure mirrors Figure 3, but with different formatting.

Figure A3
Tax Evasion as Function of Bribery (Mass)



Note:
The figure is a scatter chart visualizing tax evasion as a function of bribery. The x-axis represents the bribe amount paid by the trader to the liquidateur official. The y-axis represents the tax-evasion amount, defined as the tax owed less the tax paid. Monetary values are in USD. The figure plots data trimmed at the top/bottom 1%. Different sized dots represent more/fewer observations at that coordinate. The sample used is all data from the latest (2021) version of our survey. The figure mirrors Figure 3, but with different formatting.

B Tables

Table A1
Balance on Officials' Demographics

	(1) Age Official	(2) Female Official
Tax Owed	0.000	-0.000
	(0.000)	(0.000)
Shipment KGs	-0.000***	0.000***
	(0.000)	(0.000)
Shipment Value	-0.000*	-0.000
	(0.000)	(0.000)
Other Trade Costs	0.000***	0.000
	(0.000)	(0.000)
Red Lane	0.740***	-0.065**
	(0.270)	(0.032)
Client Shipments/Y	-0.009	-0.001*
	(0.009)	(0.001)
Client Employees	0.009	0.001
	(0.007)	(0.001)
Origin=Central & South America.	-1.995***	0.056
	(0.768)	(0.168)
Origin=China.	-0.366	0.018
	(0.329)	(0.031)
Origin=North America.	2.161	-0.002
	(1.621)	(0.110)
Origin=Other Asia.	0.360	0.084*
	(0.522)	(0.046)
Origin=Other Europe.	-0.223	0.078**
	(0.342)	(0.035)
Origin=Other Middle East & North Africa.	0.921	-0.073**
	(0.699)	(0.032)
Origin=Sub-Saharan Africa.	-3.144***	-0.081*
	(0.596)	(0.048)
Origin=Turkey.	-0.036	0.011
	(0.294)	(0.027)
Client=European Union.	1.128	-0.017
	(1.730)	(0.098)
Client=North America.	3.304*	0.344***
	(1.700)	(0.118)
Client=Other Europe.	0.139	0.481***
	(0.548)	(0.171)
Client=Turkey.	0.846***	0.315***
	(0.282)	(0.033)
Outcome Mean	49	0.17
Observations	1,358	1,358
R^2	0.330	0.123
Month-by-Year FE	YES	YES
Official Controls	YES	YES

Note:
The table shows our "balance" test of the random assignment of officials to shipments. The dependent variables are official demographics, namely age and gender. The independent variables are the other official characteristics (age or gender, rank, tenure, and liquidateur/reviseur status), month-by-year fixed effects, and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, origin, client employees, client trade volume, client nationality). Monetary values are in USD. In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The sample used is all data from the latest (2021) version of our survey.

Table A2
Balance on No. Matches

	No. Matches
Tax Owed	0.000
	(0.000)
Shipment KGs	-0.000***
	(0.000)
Shipment Value	-0.000
	(0.000)
Other Trade Costs	-0.000
	(0.000)
Red Lane	1.020***
	(0.350)
Client Shipments/Y	0.044***
	(0.012)
Client Employees	-0.033***
	(0.011)
Origin=Central & South America.	0.474
	(1.206)
Origin=China.	-0.915*
	(0.509)
Origin=North America.	-1.552
	(0.944)
Origin=Other Asia.	0.089
	(0.628)
Origin=Other Europe.	-1.185**
	(0.577)
Origin=Other Middle East & North Africa.	-0.379
	(0.654)
Origin=Sub-Saharan Africa.	-6.895***
	(1.186)
Origin=Turkey.	0.028
	(0.454)
Client=European Union.	0.455
	(0.767)
Client=North America.	7.537***
	(1.384)
Client=Other Europe.	-1.277
	(0.867)
Client=Turkey.	1.114
	(1.745)
Outcome Mean	14
Observations	1,358
R^2	0.824
Trader FE	YES
Month-by-Year FE	YES
Official Controls	YES

Note:
The table shows our "balance" test of the random assignment of officials to shipments. The dependent variable is the number of matches between the trader and the official to whom they are believed to have been randomly assigned. The independent variables are trader fixed effects, month-by-year fixed effects, official controls (age, gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, origin, client employees, client trade volume, client nationality). Monetary values are in USD. In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The sample used is all data from the latest (2021) version of our survey.

Table A3
Effect of Officials' Demographics on Bribery and Tax Evasion (Fewer Controls)

	(1)	(2)	(3)	(4)	(5)	(6)
	Bribe Yes/No			Tax Paid (Log)		
Panel A: Age						
Age Official	0.010***	0.010***	0.016***	0.043***	0.025***	0.011***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)
Panel B: Gender						
Female Official	0.032	0.030	0.007	-0.172*	-0.134*	0.011
	(0.032)	(0.030)	(0.027)	(0.088)	(0.074)	(0.045)
Outcome Mean		.57			9.5	
Observations	1,422	1,360	1,358	1,423	1,361	1,358
R^2	0.001	0.230	0.400	0.003	0.418	0.722
Trader FE	NO	NO	YES	NO	NO	YES
Official Controls	NO	NO	YES	NO	NO	YES
Month-by-Year FE	NO	YES	YES	NO	YES	YES
Shipment Controls	NO	YES	YES	NO	YES	YES

Note:
The table shows additional regression results for the effect of officials' demographics on bribery and tax evasion. Observations are at the official-level. In Columns 1-3, the dependent variable is an indicator for whether a bribe was exchanged. In Columns 4-6, the dependent variable is the log of the amount of tax paid. In Panel A, which represents its own set of regressions, the independent variable of interest is official age, coded as ten-year bins. In Panel B, which represents its own set of regressions, the independent variable of interest is official gender, coded as a female indicator. Monetary values are in USD. The controls include trader fixed effects, month-by-year fixed effects, other official controls (age or gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, client employees, and client trade volume). In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The sample used is all data from the latest (2021) version of our survey. The table mirrors Table 4, but with different sets of controls.

Table A4
Effect of Officials' Demographics on Bribery and Tax Evasion (Trader FEs)

	(1) Bribe Yes/No	(2) Tax Paid (Log)
Age Official	0.001	0.002
	(0.001)	(0.003)
Female Official	0.017	0.003
	(0.020)	(0.042)
Outcome Mean	.57	9.52
Observations	1,358	1,358
R^2	0.714	0.757
Month-by-Year FE	YES	YES
Trader FE	YES	YES
Controls	YES	YES

Note:
The table shows additional regression results for the effect of officials' demographics on bribery and tax evasion. Observations are at the official-level. In Column 1, the dependent variable is an indicator for whether a bribe was exchanged. In Column 2, the dependent variable is the log of the amount of tax paid. The independent variables of interest are official age and gender, coded as ten-year bins and a female indicator respectively. Monetary values are in USD. The other controls include trader fixed effects, month-by-year fixed effects, other official controls (age or gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, client employees, and client trade volume). In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The sample used is all data from the latest (2021) version of our survey. The table mirrors Table 4, but with trader fixed effects.

Table A5
Effect of No. Matches on Bribe Probability

	Bribe Yes/No
No. Matches (Liquidateur)	0.000
	(0.001)
No. Matches (Reviseur)	-0.002*
	(0.001)
Outcome Mean	.57
Observations	1,358
R^2	0.714
Trader FE	YES
Month-by-Year FE	YES
Controls	YES

Note:
The table shows additional regression results for the effect of the number of matches on bribery and tax evasion. Observations are at the official-level. The dependent variable is an indicator for whether a bribe was exchanged. The independent variables of interest are the number of matches between the trader and the official originally assigned to the trader, for both the liquidateur and the reviseur. The controls include trader fixed effects, month-by-year fixed effects, official controls (age, gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, client employees, and client trade volume). In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The sample used is all data from the latest (2021) version of our survey.

Table A6
Effect of No. Matches on Tax Evasion (Log Control)

	Tax Paid (Log)
No. Matches (Liquidateur)	0.001
	(0.001)
No. Matches (Reviseur)	0.000
	(0.000)
Tax Owed (Log)	0.998***
	(0.008)
Outcome Mean	9.52
Observations	1,358
R^2	0.986
Trader FE	YES
Month-by-Year FE	YES
Controls	YES

Note:
The table shows additional regression results for the effect of the number of matches on tax evasion. Observations are at the official-level. The independent variables of interest are the number of matches between the trader and the official originally assigned to the trader, for both the liquidateur and the reviseur. Monetary values are in USD. The controls include the log of the amount of tax owed, trader fixed effects, month-by-year fixed effects, official controls (age, gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, client employees, and client trade volume). In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The sample used is all data from the latest (2021) version of our survey. The table mirrors Table Table 5, but controls for tax owed in logs instead of linearly.

Table A7
First-Stage Predicting Terminal Official with Original Official

	Terminal Matches
Original Matches	0.905***
	(0.009)
Observations	1,423
R^2	0.892

Note:
The table shows the first-stage regression of "Matches Original" (the number of matches with the randomly assigned official) on "Matches Terminal" (the number of matches with the official with whom the trader actually ended up working). Observations are at the official-level. In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The sample used is all data from the latest (2021) version of our survey.

Table A8
Effect of No. Matches on Bribery and Tax Evasion (TOT)

	(1) Esp. Friendly Yes/No	(2) Bribe (Log)	(3) Tax Paid (Log)
No. Matches (Liquidateur)	0.012***	-0.011**	-0.011**
	(0.004)	(0.005)	(0.005)
No. Matches (Reviseur)	0.000	0.014**	0.002
	(0.003)	(0.006)	(0.003)
Outcome Mean	.33	7.15	9.52
Observations	1,358	769	1,358
R^2	0.423	0.793	0.755
Trader FE	YES	YES	YES
Month-by-Year FE	YES	YES	YES
Controls	YES	YES	YES

Note:
The table shows additional regression results for the effect of the number of matches on bribery and tax evasion. Observations are at the official-level. In Column 1, the dependent variable is the relationship quality between the official and the trader (which is a question in our questionnaire that asks yes/no whether the trader has an especially friendly relationship with the official). In Column 2, the dependent variable is the log of the bribe amount, conditional on a bribe being exchanged. In Column 3, the dependent variable is the log of the amount of the tax paid. The independent variables of interest are the number of matches between the trader and the "Terminal" official who actually ended up working with the trader, instrumented by the "Original" official who was randomly assigned, for both the liquidateur and the reviseur. Monetary values are in USD. The controls include trader fixed effects, month-by-year fixed effects, official controls (age, gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, other trade costs, red-lane assignment, client employees, and client trade volume). In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The sample used is all data from the latest (2021) version of our survey. The table mirrors Table 5, but instead of showing ITT specifications it shows TOT specifications.

Table A9
Effect of No. Matches on Bribery and Tax Evasion (100% Sample & No I.V.)

	(1) Esp. Friendly Yes/No	(2) Bribe (Log)	(3) Tax Paid (Log)
No. Matches (Liquidateur)	0.019***	-0.005	-0.009**
	(0.003)	(0.004)	(0.004)
No. Matches (Reviseur)	-0.011***	0.007	0.002
	(0.002)	(0.004)	(0.003)
Draw No.	0.118***	0.075*	0.063**
	(0.040)	(0.043)	(0.029)
Outcome Mean	0.33	7.02	9.48
Observations	1,358	769	1,358
R^2	0.434	0.794	0.756
Trader FE	YES	YES	YES
Month-by-Year FE	YES	YES	YES
Controls	YES	YES	YES

Note:
The table shows additional regression results for the effect of the number of matches on bribery and tax evasion. Observations are at the official-level. In Column 1, the dependent variable is the relationship quality between the official and the trader (which is a question in our questionnaire that asks yes/no whether the trader has an especially friendly relationship with the official). In Column 2, the dependent variable is the log of the bribe amount, conditional on a bribe being exchanged. In Column 3, the dependent variable is the log of the amount of the tax paid. The independent variables of interest are the number of matches between the trader and the official originally assigned to the trader, for both the liquidateur and the reviseur. Monetary values are in USD. The other controls include trader fixed effects, month-by-year fixed effects, official controls (age, gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, other trade costs, red-lane assignment, client employees, and client trade volume), and draw number (an indicator for whether the official worked with the randomly assigned "Original" inspector versus a different non-randomly assigned "Terminal" inspector). In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The table mirrors Table 5, but (1) it uses all data from all versions of our survey (2019-2021), and (2) instead of using instrumental-variables it controls for draw number.

Table A10
Effect of No. Matches on Bribery and Tax Evasion (Fewer Controls)

	(1)	(2)	(3)	(4)	(5)	(6)
	Esp. Friendly Yes/No		Bribe (Log)		Tax Paid (Log)	
No. Matches (Liquidateur)	0.009***	0.009***	-0.013***	-0.008**	-0.006	-0.008**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
No. Matches (Reviseur)	0.001	0.001	0.011**	0.010**	0.002	0.001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Outcome Mean	0.33		7.2		9.5	
Observations	1,420	1,358	814	769	1,420	1,358
R^2	0.492	0.504	0.772	0.794	0.733	0.755
Trader FE	YES	YES	YES	YES	YES	YES
Month-by-Year FE	NO	YES	NO	YES	NO	YES
Official Controls	YES	YES	YES	YES	YES	YES
Shipment Controls	NO	YES	NO	YES	NO	YES

Note:
The table shows additional regression results for the effect of the number of matches on bribery and tax evasion. Observations are at the official-level. In Columns 1-2, the dependent variable is the relationship quality between the official and the trader (which is a question in our questionnaire that asks yes/no whether the trader has an especially friendly relationship with the official). In Column 3-4, the dependent variable is the log of the bribe amount, conditional on a bribe being exchanged. In Column 5-6, the dependent variable is the log of the amount of the tax paid. The independent variables of interest are the number of matches between the trader and the official originally assigned to the trader, for both the liquidateur and the reviseur. Monetary values are in USD. The controls include trader fixed effects, month-by-year fixed effects, official controls (age, gender, rank, tenure, and liquidateur/reviseur status), and shipment controls (weight, value, tax owed, other trade costs, red-lane assignment, client employees, and client trade volume). In the parentheses are robust standard errors clustered at the shipment level. (*** p¡0.01, ** p¡0.05, * p¡0.1.) The sample used is all data from the latest (2021) version of our survey. The table mirrors Table 5, but with different sets of controls.

C Proofs

C.1 Nash Bargaining Equilibrium Equivalence

Recall that the trader's and the official's utilities (with and without tax evasion) and the joint surplus from tax evasion are defined as follows.

$$
\begin{aligned}
U_T^0(t, b; \tilde{t}) &= -\tilde{t} \\
U_T^1(t, b; \tilde{t}) &= -t - \alpha(\tilde{t} - t)^2 - b \\
U_O^0(t, b; \tilde{t}) &= 0 \\
U_O^1(t, b; \tilde{t}) &= -\beta(\tilde{t} - t)^2 + b \\
S(t; \tilde{t}) &= (\tilde{t} - t) - \alpha(\tilde{t} - t)^2 - \beta(\tilde{t} - t)^2
\end{aligned}
$$

And recall that equilibrium taxes paid are as follows.

$$
t^* = \tilde{t} - \frac{1}{2}\frac{1}{\alpha + \beta}
$$

Hence the utility and surplus terms evaluated at equilibrium taxes paid are as follows.

$$
\begin{aligned}
U_T^0(t^*, b; \tilde{t}) &= -\tilde{t} \\
U_T^1(t^*, b; \tilde{t}) &= -(\tilde{t} - \frac{1}{2}\frac{1}{\alpha + \beta}) - \alpha(\tilde{t} - (\tilde{t} - \frac{1}{2}\frac{1}{\alpha + \beta}))^2 - b \\
U_O^0(t^*, b; \tilde{t}) &= 0 \\
U_O^1(t^*, b; \tilde{t}) &= -\beta(\tilde{t} - (\tilde{t} - \frac{1}{2}\frac{1}{\alpha + \beta}))^2 + b \\
S(t^*; \tilde{t}) &= (\tilde{t} - (\tilde{t} - \frac{1}{2}\frac{1}{\alpha + \beta})) - \alpha(\tilde{t} - (\tilde{t} - \frac{1}{2}\frac{1}{\alpha + \beta}))^2 - \beta(\tilde{t} - (\tilde{t} - \frac{1}{2}\frac{1}{\alpha + \beta}))^2
\end{aligned}
$$

Let b_1^* be the bribe that solves the Nash Product optimization problem.

$$
b_1^* = \text{argmax}[U_T^1(t^*, b; \tilde{t}) - U_T^0(t^*, b; \tilde{t})][U_O^1(t^*, b; \tilde{t}) - U_O^0(t^*, b; \tilde{t})]
$$

Substituting the utility terms evaluated at equilibrium taxes paid, taking first-order conditions, and rearranging algebraically yields the following.

$$
b_1^* = \frac{\alpha + 3\beta}{8(\alpha + \beta)^2}
$$

Let b_2^* be the bribe such that the players' utilities with tax evasion are the same as their utilities without tax evasion (their "outside options") plus one half of the joint surplus.

$$\begin{aligned} U_T^1(t^*, b_2^*; \tilde{t}) &= U_T^0(t^*, b_2^*; \tilde{t}) + \gamma S(t^*; \tilde{t}) \\ U_O^1(t^*, b_2^*; \tilde{t}) &= U_O^0(t^*, b_2^*; \tilde{t}) + (1-\gamma) S(t^*; \tilde{t}) \\ \text{s.t. } \gamma &\equiv 1 - \gamma \equiv \frac{1}{2} \end{aligned}$$

Substituting the utility and surplus terms evaluated at equilibrium taxes paid and rearranging algebraically yields the following.

$$b_2^* = \frac{\alpha + 3\beta}{8(\alpha+\beta)^2}$$

$b_1^* = b_2^*$ and therefore the two Nash Bargaining equilibria are equivalent.

C.2 Bribe-Match Comparative Statics

Recall that the derivative of equilibrium bribes with respect to matches is composed of five terms, which we can label Z, A1, A2, B1, and B2.

$$\frac{\partial b^*(\alpha(u(m)), \beta(u(m)))}{\partial m} = \underbrace{\frac{1}{8(\alpha+\beta)^3}}_{\text{Z}} [\underbrace{\alpha'}_{\text{A1}} \underbrace{(-\alpha - 5\beta)}_{\text{A2}} + \underbrace{\beta'}_{\text{B1}} \underbrace{(-\alpha + 3\beta)}_{\text{B2}}]$$

Z is positive, A1 is negative, A2 is negative, B1 is negative, and B2 is either positive or negative. Hence the sign of the derivative depends entirely on the sign of B2.

$$\frac{\partial b^*(\alpha(u(m)), \beta(u(m)))}{\partial m} = \underbrace{\frac{1}{8(\alpha+\beta)^3}}_{+} [\underbrace{\alpha'}_{-} \underbrace{(-\alpha - 5\beta)}_{-} + \underbrace{\beta'}_{-} \underbrace{(-\alpha + 3\beta)}_{?}]$$

If B2 is negative, then B1×B2 is positive, and then the derivative is positive and bribes are increasing in matches. If B2 is positive, then B1×B2 is negative, and then the sign of the derivative depends on the following inequality.

$$
\begin{aligned}
\alpha'(-\alpha - 5\beta) + \beta'(-\alpha + 3\beta) &< 0 \\
\Rightarrow \beta'(-\alpha + 3\beta) &> \alpha'(-\alpha - 5\beta) \\
\Rightarrow \frac{\beta'}{\alpha'} &> \frac{\alpha + 5\beta}{\alpha - 3\beta} \\
\Rightarrow \frac{\partial b^*(\alpha(u(m)), \beta(u(m)))}{\partial m} &< 0
\end{aligned}
$$