Speed Money: Time, Corruption, and Trade

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Abstract

This paper shows that longer trade times are associated with higher levels of trade-related corruption, consistent with a theoretical framework in which "fast" producers earn higher profits than "slow" ones, but may have to pay "speed money" to possibly corrupt customs officials. This finding is robust to the use of corruption measures based on perceptions and reported behavior, the inclusion of a wide range of control variables from the previous literature, and estimation by a variety of methods including instrumental variables. Moreover, results from a gravity model show that the combination of slow border procedures and rampant corruption acts as a significant drag on international trade, in line with the model's predictions: the elasticity of bilateral trade with respect to trade time is around 5% stronger in a country with rampant corruption compared with a corruption free country. Together, these results suggest that improved trade facilitation can be an effective and feasible policy for reducing corruption over the short-term in weak institutional environments.

JEL Codes: F13; O24; P48.

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"I hope to be reborn as a customs official..."

CEO of a successful Thai manufacturing company[1]

1 Introduction

There is no lack of empirical evidence on the negative effects of corruption in developing countries. Higher corruption rates have been found to inhibit trade (Anderson and Marcouiller, 2002), as well as investment and growth (Mauro, 1995). Current policy discourse, as evidenced by the recent controversy over the World Bank's new corruption and governance policy, tends to emphasize improved detection and enforcement capacities, along with a possible role for sanctioning behavior by international organizations, as the primary policy tools for dealing with corruption in poor countries. However, such an approach in a sense just re-poses the whole "development question": if poor countries had strong institutions, or could develop them quickly and inexpensively, they would probably already have reached a less harmful corruption equilibrium, as is the case in most developed economies. Similarly, much analytical work on the causes of corruption tends to focus on deep institutional or cultural characteristics that can only be changed very slowly (e.g., Treisman, 2000).

This paper takes a different approach. It emphasizes the potential for one particular policy measure–improved trade facilitation–to reduce the prevalence and negative effects of trade-related corruption. While obviously not a cure-all for the wide variety of corrupt transactions taking place in many economies, I show that trade facilitation can nonetheless be of considerable help in dealing with trade-related corruption. Moreover, trade facilitation policies are relatively quick and inexpensive to implement compared with fundamental institutional changes.

Customs and border control agencies play a vital gate keeping role at the interface between national and international markets. Beyond questions of security and public safety, customs officers can have considerable de facto power to influence the operations of trading firms. In some cases at least, that power can be abused in order to obtain significant economic benefits–witness the Thai CEO's eagerness to change places with a civil servant in the quotation above. As an example of the order of magnitude

[1] Cited in Svensson (2005).

of the gains involved, Sequiera and Djankov (2009) find that corrupt payments can represent up to a 600% increase in the monthly salary of a port official in Southern Africa. This paper focuses on "speed money"–an unofficial payment to customs and border agents in order to "facilitate" speedy clearance of goods–as one mechanism by which this kind of enrichment might take place, and finds strong evidence that it is an important and trade-inhibiting phenomenon.

In these days of lean retailing and just-in-time manufacturing, time is becoming ever more important as a potential trade barrier. Using a gravity model of bilateral trade, Djankov et al. (2008) show that reducing the time taken to export by one day can increase bilateral trade by around 1%. Hummels (2001) uses US import data to show that increasing trade time by one day can decrease the probability that the US sources from that country by 1-1.5%. In the clothing and apparel industry, Evans and Harrigan (2005) find evidence that patterns of global sourcing from the US are heavily influenced by geographical proximity, which they interpret in terms of the speed with which goods can be moved between markets.

Although there is already extensive evidence that trading firms are willing to make unofficial payments in order to evade some kinds of trade-related regulatory burdens, this paper is one of the first to analyze the links between corruption and trade times. Higher tariff rates have repeatedly been shown to be associated with higher levels of corruption, as firms are incentivized to make unofficial payments in exchange for border officers failing to assess duty on imports (Fisman and Wei, 2004; Dutt, 2009). In addition, Fisman and Wei (2007) show that controls on trading in certain types of goods, such as cultural artifacts, can also create an incentive to engage in corrupt behavior.

The empirical literature contains some suggestive evidence of a link between corruption and trade times, based on region-specific surveys of trading firms. For example, Das and Pohit (2006) survey traders on the India-Bangladesh border, and find that the majority of exporters make speed money payments of between one and three percent of shipment value; some report paying as much as 10%. In a study of the ports of Durban (South Africa) and Maputo (Mozambique), Sequiera and Djankov (2009) find that queue jumping and avoiding storage costs (as well as tariff evasion) are important motivations for many corrupt transactions.

Against this background, the present paper makes two main contributions. First, it examines for the first time the links between trade time and corruption in a cross-country framework. It thus builds on the region-specific surveys discussed above (Das and Pohit, 2006; Sequiera and Djankov, 2009), as well as previous cross-country work on the determinants of corruption that focuses on different explanatory variables, particularly tariffs (Dutt, 2009). Using data for over 100 countries, I show that there is a strong, significant, and robust link between longer trade times and more trade-related corruption.

Second, the paper uses a gravity model to provide additional evidence on the links between trade times and corruption through their combined effect on bilateral trade flows. Results strengthen those from the cross-country regressions: corruption and trade time are both negatively associated with bilateral trade, as is their interaction. These findings are in line with those of Anderson and Marcouiller (2002)–who do not use an interaction term–and Dutt and Traca (Forthcoming) who interact corruption with tariff rates.

The paper proceeds as follows. In the next section, I sketch out a simple conceptual framework that highlights the links between official trade times and corrupt payments. Section 3 presents data on corruption and trade times, and conducts a preliminary analysis using nonparametric methods. In Section 4, I conduct cross-country regressions of the determinants of trade-related corruption, and undertake extensive robustness checks covering country samples, potential omitted variables, and estimation methods. Section 5 presents a gravity model of bilateral trade, and uses it to provide corroborating evidence for the cross-country regression findings in Section 4. Section 6 concludes, discusses policy implications, and presents some avenues for further research in this area.

2 Conceptualizing Speed Money

An incentives-based model of corruption provides a useful framework for understanding the political economy of speed money, and developing a number of testable hypotheses (cf. Bardhan, 2006). In this section, I present the model informally in order to make the intuition clear.[2] Full details are set out in the Appendix. In essence, the model combines the "lean retailing" framework of Evans and Harrigan (2005)

[2]Of course, the model presented here focuses on just one mechanism–responsiveness to demand shocks–that can make lower trade time valuable, and thereby lead to corruption. Another possible mechanism could be the gains from being part of a transnational production network, access to which is only possible for firms that can ship goods quickly. Time sensitivity of the goods exported, for instance due to perishability, could also create a similar dynamic. Alternatively, reliance on imported intermediates could be combined with demand uncertainty and inventory costs. I leave it to future work to examine these possibilities in more detail.

with a simple rent-sharing model of bribery. The basic mechanism is straightforward. The ability to produce and ship goods more quickly is commercially valuable to firms, since it enables them to respond more fully to demand shocks. However, customs agents play a gatekeeper role because they control the speed with which goods can move from producers to consumers. Corrupt customs agents can extract a "gift" from firms looking to use the fast track, reflecting the commercial value of speed to producers.

Previous theoretical work on corruption and trade has largely focused on the case of tariffs rather than time. For example, Dutt and Traca (Forthcoming) develop a model in which officials choose endogenously between extortion or evasion behaviors, driven in part by the prevailing level of tariffs. The setup in the model presented here differs from theirs in that I focus on the value of trade time to producers rather than the value of avoiding tariffs, and constrain the behavior of officials to reflect the evasion paradigm only. In the broader literature on corruption, Ades and Di Tella (1999) emphasize the importance of rents, using natural resources or imperfect competition in product markets as examples. I consider a different source of rents, namely the difference in expected profits that comes from enabling faster delivery times. Lui (1985) and Batabyal and Yoo (2007) consider bribery in the context of a queuing model. Different opportunity costs of time across individuals drive selection into bribery. The model presented here abstracts from queuing theory, but provides some micro-foundations for the existence of different opportunity costs of time that lead firms to self-select into those that pay speed money, and those that do not.

2.1 Model Setup

There are two firms, each of which is a monopolist with an identical inverse demand curve. Both firms are located in the same country, but produce goods exclusively for export (i.e., local demand is zero). Firm location is exogenous and fixed. Their export market can be considered an aggregate "rest of the world" region with no fixed or variable trade costs between any countries. Labor is the only factor of production, and is in perfectly elastic supply at the prevailing wage rate (normalized to unity).

Firms maximize the expected profits from sales over two periods. Demand in each period is stochastic. Low and high demand realizations occur with fixed probabilities. Output can be stored costlessly between periods, but inventory left over at the end of the second period has zero value.

The only difference between the two firms is the rate at which they can produce and ship goods to the rest of the world. One firm ("slow") can only produce and ship once in a two period model cycle. The other firm ("fast") can produce and ship twice over the same time frame. Being fast is advantageous, since demand is realized twice in the model, and a fast firm can therefore respond more fully to demand shocks than a slow firm. As in Evans and Harrigan (2005), the ex ante expected profit functions of both firms are increasing in the variance of demand, but the rate of increase is more rapid for the fast firm.

To be able to export its goods more frequently than the slow firm, the fast firm must deal with customs agents, who control access to the export "fast track". Some of these officials may be corrupt, and will require the fast firm to make a gift ("speed money"). The fast firm therefore faces higher expected production and shipping costs than the slow firm, since it must incorporate the probability of having to deal with a corrupt customs official, and the amount of speed money that would have to be paid in that case.

For customs agents, the decision whether or not to be corrupt (i.e., accept speed money) is made endogenously at the beginning of the model cycle. An individual customs agent balances a certain wage income from being honest against an uncertain wage and gift income from being dishonest. The uncertainty in the latter case arises from there being a fixed probability that the official's corrupt conduct will be detected and punished, in which case she earns zero. The model assumes that officials also gain utility through an "honesty bonus", in which there is a subjective psychological or social gain from following rules and "doing the right thing". The honesty bonus is distributed randomly across customs agents according to a given distribution. The proportion of customs agents who are corrupt is given by the proportion of that distribution falling below the minimum level of honesty bonus consistent with optimal refusal of speed money.

Finally, the model assumes that if the fast firm must deal with one of the customs agents who is corrupt, then the official has full bargaining power. As a result, the speed money that she is able to extract amounts to the full difference in ex ante expected profits between the slow and fast firms. This is the highest possible level of gift that is consistent with the fast firm not making a loss.

2.2 Equilibrium

By analogy with Evans and Harrigan (2005), the model's timing is as follows:

1. Customs agents decide whether or not to be corrupt, and choose the "gift" required in order to secure quick passage of goods through customs.

2. Firms decide how much to produce.

3. Period 1 demand is realized, and firms decide how much to sell in period 1. Unsold production is carried over costlessly to period 2.

4. The fast firm produces again. The slow firm does not.

5. Period 2 demand is realized, and firms decide how much to sell in period 2. Unsold production is discarded.

As shown in the Appendix, the model can be solved by backwards induction. Equilibrium consists of a vector of parameters summarizing optimal levels of production and sales by both firms, the amount of the gift required by corrupt customs agents for fast track treatment, and the proportion of customs agents who are corrupt. At the margin, customs agents are indifferent between being corrupt or honest, and the ex ante expected profits of the slow and fast firms are equalized.

2.3 Comparative Statics and Testable Hypotheses

The model's equilibrium structure and comparative statics provide a number of interesting, and testable, predictions as to the factors that influence trade-related corruption. (Comparative statics are discussed in detail in the Appendix.) First, the incentive for the payment of speed money in this model comes from the ability of the fast firm to respond more fully to overseas demand shocks, and thereby to have higher ex ante expected profits than the slow firm. It is thus the existence of a delay–reflected in the inability of the slow firm to produce and ship twice per cycle–and the ability of customs agents to circumvent such delays for the fast firm, that drives the existence of a corruption equilibrium. The existence of time delays facing traders should therefore be associated with the prevalence of trade-related corruption. This is the core hypothesis of interest in this paper, and it is tested using cross-country data in Section 4.

Second, the model suggests that a country's governance characteristics have a role to play in reducing trade-related corruption prevalence. In terms of the theory, an increased probability of detection and punishment are associated with less prevalent corruption. Two aspects of this linkage are tested using cross-country data in Section 4, namely: that increased government effectiveness, in the sense of stronger bureaucratic controls and improved law enforcement, are associated with less prevalent corruption; and that increased voice and accountability of office holders, which makes denunciation of corrupt activity more likely, is also associated with less prevalent corruption.

Third, there is also a link between corruption prevalence and cultural attitudes, in particular the average premium that individuals place on honesty or "doing the right thing". A higher level of cultural intolerance of corruption is associated with a lower level of corruption prevalence. Again, I test this hypothesis using cross-country data in Section 4.

In addition to these directly testable hypotheses, the model also suggests another way of examining the links between corruption and trade time based on their effects on international trade flows. The Appendix shows that the effect of corruption on bilateral trade depends on the extent of the difference in ex ante expected profits between the fast firm and the slow one in the absence of corruption. This, in turn, depends on the level of time delay affecting the slow firm, and which the fast firm circumvents. As a result, the model suggests that the interaction of corruption and trade time should be a significant determinant of bilateral trade flows, and should carry a negative sign. I test this hypothesis using a gravity model in Section 5.

3 Data and Non-Parametric Analysis

The theoretical framework presented above suggests an empirical model in which trade-related corruption is a function of the set of incentives facing customs agents and traders. The importance of trade times, governance, and cultural attitudes has already been highlighted. In the empirical work that follows, I therefore postulate:

$$corruption_i = f\left(time_i, govt.effectiveness_i, accountability_i, culture_i, e_i\right) \quad (1)$$

where e_i is a random error term satisfying standard assumptions.

After first presenting two empirical measures of trade-related corruption, this section discusses data on each of these factors in turn, and presents some preliminary evidence of their links with corruption. (See Table 1 for a full listing of data and sources.)

3.1 Corruption Data

The most common empirical approach to measuring corruption has been to use perception indices.[3] A number of such indices are available, for instance from Transparency International or the World Economic Forum. Although differing in the details, the approach for all perception indices is basically similar. Company executives, or another group thought to have first hand knowledge of corrupt transactions, are asked to rate corruption according to a numerical scale. Individual responses are then aggregated up to the country level, usually by averaging. The advantage of these data is that each index is usually maintained by one organization over a substantial period of time, so the questions asked of survey participants tend to remain quite similar from one year to the next. As Ades and Di Tella (1999) point out, these data do not suffer from the comparability problems that can arise when using law enforcement data, for example due to differing legal definitions of corruption. Another advantage is that these indices are usually available for a relatively large number of countries. However, there are also a number of difficulties in relying exclusively on perception indices as a measure of corruption on the ground. It can be difficult to distinguish genuine cross-country and year-on-year variation in corruption from statistical noise, due to the sampling error inherent in the use of survey data with a limited number of participants, as well changes in the identity of participants from one year to the next. Nonetheless, recent work by Olken (Forthcoming) and Fisman and Wei (2007) confirms that there is some degree of correspondence between perceptions of corruption and reality on the ground, albeit one that is subject to numerous caveats and

[3] Alternative approaches to analyzing corruption include: inference based on trade data (Fisman and Wei, 2004; 2007); firm-level surveys with binary response or quantitative data on corrupt transactions (Svensson, 2003); direct observation (Olken and Barron, Forthcoming); and experiments (Olken, 2007).

limitations.

In line with previous work, the main empirical results in this paper are based on perception data. I use a survey question from the World Economic Forum (WEF) Executive Survey that asks respondents to use a one to seven scale to indicate how commonly firms in their industry give irregular payments or bribes in connection with import and export permits. I rescale these data so that a response of one corresponds to "never", and seven corresponds to "commonly". Due to the specificity of the survey question used, this index should suffer as little as possible from the measurement error that can plague the use of corruption indicators like the Transparency International index which are not specific to particular sectors or activities.

I also perform a robustness check using firm-level data from the World Bank's Enterprise Survey (WBES). Since all other factors that I am interested in vary at the country level, I aggregate the WBES data to give the percentage of respondent firms in each country indicating that a gift or informal payment was asked for or expected to obtain an import permit. Although this kind of measure inevitably poses its own difficulties, in particular the possibility of under-reporting due to a perceived risk of punishment, previous work suggests that firms tend to be reasonably forthcoming in practice (Svensson, 2003). For the purposes of this paper, the most pressing constraint in relation to the WBES data is in fact country coverage: only 71 countries have usable data for this survey question, compared with 121 for the WEF perception index. Nonetheless, Figure 1 suggests that in so far as the two measures overlap, they appear to be capturing some common features of reality: the simple correlation coefficient between the WEF measure (in logarithms) and the WBES measure is 0.45 across 57 observations.

3.2 Trade Times

Djankov et al. (Forthcoming) introduce a new database of trade times, assembled under the auspices of the World Bank's Doing Business (DB) project. They collect data from 345 freight forwarders in 146 countries on the average time it takes to import or export a standard 20-foot container of goods in 2005. Respondents are given a detailed hypothetical setting out the nature of the goods and firms involved, as well as their location. They are asked to respond on the basis of the average time taken to complete all official procedures required to move the goods from a factory in the most populous city to a ship at the most accessible port. The trading process is broken down into stages, and respondents are asked to supply information on cost, time, and the number of documents involved in each step. Extensive quality control is undertaken, including follow up calls with all respondents to ensure consistent coding, and comparison with data supplied by port authorities and customs officials in 48 countries.

It is important to highlight that the DB data are intended to capture only the official times involved in importing and exporting. They are not intended to track the actual times that firms face on a day-to-day basis, which are highly likely to be contaminated by the influence of corruption in many countries. Assuming that the influence of corruption and bureaucratic harassment have been purged from the data in so far as possible, the DB data should represent something close to a firm's outside option when dealing with customs officials, i.e. the time that importing or exporting would take in the absence of any corrupt activity. To stress this point, Figure 2 plots the DB import time data against survey data from the World Bank's Logistics Performance Index (LPI) and WBES datasets. The LPI/WBES data represent the median import time reported by firms in a standard survey, and are based on actual experience rather than official requirements. Even taking account of the fact that the two data sources measure slightly different concepts–customs clearance times (LPI) versus total import times (DB)–it is remarkable that in all cases, the DB import times are substantially higher than those actually reported by surveyed firms. This is fully consistent with the interpretation just given of the difference between the two, and suggests that the DB data should be relatively free of the impact of corruption; in any case, this is an issue I return to in the context of robustness checks (see below), where I conduct instrumental variables regressions to deal with this possibility more thoroughly.

To get a preliminary idea of the relationship between trade times and corruption, I perform a non-parametric regression using locally weighted scatterplot smoothing (Lowess). The dependent variable is the WEF corruption index, and the independent variable is the average of DB export and import times (both in logarithms). Results in Figure 3 clearly support the core hypothesis of this paper, namely that higher trade times are associated with more corruption. The relationship between the two variables is consistently upward sloping, although it levels off as trade times become very long. There is also some limited evidence of nonlinearity.

3.3 Governance Institutions

The theoretical model suggests that country-level governance characteristics are also likely to be important determinants of the incentives facing potentially corrupt agents. More effective governments are likely to have greater detection and enforcement capacities, while a higher level of citizen involvement in political life likely correlates with increased risk that a corrupt customs agent will be denounced to the authorities. Both factors are associated with a higher probability of detection in terms of the theoretical model presented in the previous section. To capture these dynamics, I use two aggregate indices from the World Governance Indicators (WGI): government effectiveness, and voice and accountability (Kaufmann et al., 2008). The first of these indices aggregates perceptions from a wide range of sources on the quality of public services, the quality and independence of the civil service, the quality of policy formulation and implementation, and the credibility of the government's policy commitments. The second index aggregates perceptions of the extent to which a country's citizens can select their own government, and enjoy freedom of expression, freedom of association, and freedom of the media.

The data again provide preliminary results that agree with expectations. Figure 4 discloses a strongly negative and highly consistent relationship between WEF corruption and WGI government effectiveness (both in logarithms). A negative relationship is also apparent in Figure 5, which relates WEF corruption to WGI voice and accountability (again, both in logarithms).[4] However, the association between voice and accountability and corruption is noticeably less consistent than that between government effectiveness and corruption.

3.4 Cultural Attitudes

Finally, cultural acceptance of corruption is also likely to be a relevant factor. Environments where corruption is socially acceptable are not likely to be conducive to denunciation of corrupt officials by private agents, nor to the effective pursuit of those officials by law enforcement agencies. Thus, the probability that corruption will be detected is lower. In addition, the non-monetary (psycho-social) costs of corruption are likely to be lower in such environments: the honesty bonus is smaller, in terms of

[4] All WGI data are rescaled by adding 2.5 prior to taking logarithms. This step is necessary to deal with negative index values.

the theoretical model presented above. To take account of these possibilities, I use data on "cultures of corruption" from Fisman and Miguel (2006) as a proxy for cultural acceptance of corruption, i.e. the inverse of the cultural value of honesty. Fisman and Miguel (2006) argue that parking infringements by national diplomats assigned to United Nations missions in New York City are a useful indicator of the extent to which different cultures tolerate corruption. Since diplomats were immune from pursuit for parking violations during the time period covered by these data, they did not have any monetary incentive to comply. The only constraints acting on them were culturally-driven attitudes to rule breaking, which Fisman and Miguel (2006) argue can provide a useful indicator of the extent to which different cultures tend to accept corruption.

The association between WEF corruption and diplomatic parking infringements as a proxy for social norms is also generally in line with expectations (Figure 6, both variables in logarithms). The relationship is upward sloping, but starts to break down at very high levels of parking violations. It also appears to be substantially weaker than the bivariate relationships disclosed by the previous Lowess plots.

4 Cross-Country Regressions

The non-parametric results presented in the previous section are suggestive of a set of relationships in the data that are consistent with expectations and previous work. However, it is important to move to a fully parametric context to ensure that these findings are robust to the inter-relationships among the independent variables, and to numerous possible intervening factors that do not appear in the theory.

The workhorse model for this part of the paper is the ordered probit. I use that approach to properly account for the ordinal nature of the WEF corruption index, which is the primary dependent variable: a score of four rather than two indicates a higher level of corruption, but it is not possible to conclude that corruption is twice as high in a country that scores four as in a country that scores two. Since the reported WEF indices are simple averages of survey responses on a one to seven scale, I round off the reported figures to the nearest integer. Corruption can therefore fall into one of seven groups, however only six groups are actually observed in practice: the highest possible score (seven) is not reported for any country in the sample.

In the ordered probit context, I treat observed $corruption_i$ in terms of a latent variable $corruption_i^*$ that is a function of the factors discussed above:

$$corruption_i^* = b_1 \ln(time_i) + b_2 \ln(govt.effect._i) + b_3 \ln(accountability_i) + b_4 \ln(culture_i) + e_i \quad (2)$$

Define a set of cutoff points c such that $corruption = 0$ if $corruption^* \leq c_1$, $corruption = 1$ if $c_1 < corruption^* \leq c_2$, and so on. With appropriate normalizations, and assuming that $e_i$is normally distributed, the set of b parameters and the cutoffs c can be estimated by standard maximum likelihood techniques.

For robustness checks using WBES corruption data, the dependent variable is the percentage of firms surveyed reporting that a gift or unofficial payment was asked for or expected to obtain an import license. I therefore estimate the baseline model using OLS as follows:[5]

$$corrupt\%_i = b_1 \ln(time_i) + b_2 \ln(govt.effect._i) + b_3 \ln(accountability_i) + b_4 \ln(culture_i) + e_i \quad (3)$$

4.1 Baseline Estimation Results

Results for the baseline model using WEF corruption data are reported in column 1 of Table 2, with the estimated cutoffs suppressed for brevity. All estimated coefficients have the predicted signs from the theoretical model in Section 2: time, and cultural acceptance of corruption are associated with increased corruption, whereas government effectiveness and accountability have the opposite effect. The coefficients on time and government effectiveness are statistically significant at the 1% level, but the remaining coefficients are not significant at conventional levels.

Standard diagnostics suggest that the baseline model has substantial explanatory power. The highest predicted probability coincides with the corruption index score actually observed in the data nearly 60% of the time ($Count\, R^2 = 0.577$), and the model substantially outperforms the strategy of simply choosing the most frequently observed outcome as the predicted outcome in each case ($Adjusted\, Count\, R^2 =$

[5]Results are nearly identical if estimation is via a Tobit model with a lower bound at zero and an upper bound at unity, or the fractional logit model of Papke and Wooldridge (1996).

0.309). Based on likelihood criteria, the model can be seen to substantially outperform the alternative of an intercept only model ($Pseudo - R^2 = 0.348$). A test of the joint hypothesis that all slope coefficients are equal to zero is rejected at the 1% level ($\chi^2_5 = 92.09$; $p\left(\chi^2\right) = 0.000$).

Since ordered Probit coefficients cannot be directly interpreted in terms of elasticities, I examine the changes in predicted probabilities associated with changes in trade times. Figure 7 shows predicted cumulative probabilities associated with different values for $time_i$, holding all other variables constant at their median values. The short dashed line indicates the probability of having a corruption index of zero or one, the dotted line shows the probability of having an index score of zero, one, or two, and so on. Moving from left to right on the graph, it is clear that higher trading times exert an economically meaningful effect on corruption, as the probability of recording a relatively low corruption score, say less than two, decreases markedly as time increases. At the minimum value for trade time in these data, the probability of having a corruption index score of two or better is over 80%, whereas at the maximum value it is less than 20%.

To reinforce these results, Figure 8 presents the predicted probability of being a relatively low corruption country (index score of one) versus being a relatively high corruption country (index score of four) for values of time between the sample minimum and maximum. The probability of being a low corruption country falls from around 50% at the minimum value of time to less than 10% at its maximum, while the probability of being a high corruption country increases from approximately zero to more than 10% over the same range. As the confidence intervals in the graph suggest, the changes are statistically significant in both cases.

Column 2 of Table 2 presents results for the baseline model using WBES corruption data. Results generally line up well with those from the ordered probit model using WEF data. The coefficient on trade time is positive and 5% significant, in line with theoretical predictions. Cultural acceptance of corruption also has the expected positive coefficient, while government effectiveness and accountability have the expected negative coefficients. Only the coefficient on government effectiveness is not statistically significant at conventional levels.

Taking these results together, the baseline estimates clearly support the hypotheses advanced above to the effect that trade time and cultural acceptance impact positively on corruption prevalence, but that government effectiveness and accountability impact negatively. Results line up reasonably well using two different sources of corruption data, one (WEF) based on perceptions, and the other (WBES) based on reported behavior by firms. However, given that the effective sample is much smaller for the WBES data than for the WEF data–74 observations versus 111–the remainder of this section presents additional results using the WEF data only.[6]

4.2 Dealing with Endogeneity

Clearly, identification is a major issue in this model. One aspect of the identification problem here is the need to exclude other country-specific factors that might be driving both trade time and corruption, and I address that issue below in the context of robustness checks. A second aspect is, of course, the potential for endogeneity bias. There are a number of possible ways in which concerns regarding endogeneity can be raised, and I deal with them in turn.

First, it might be thought that the DB trade time data might reflect the faster trade times obtained by corrupt firms, since such firms may have been included in the DB survey. Thus, an unexpected shock to corruption prevalence would feed through to faster reported trade times, and tend to bias the coefficient on trade time towards zero. For the reasons set out in Section 3, it is unlikely that the DB data in fact suffer from this problem, since they are designed to reflect official times only–the best available proxy of a trader's outside option if she decides not to pay speed money. Beyond definitions, however, this is also an issue that can be addressed empirically, since if the argument put forward in favor of the exogeneity of DB data is correct, other data collected in a different manner should demonstrate stronger evidence of a coefficient biased towards zero. I therefore re-run the baseline model using the shortest import times (averaged by country) reported by survey participants in the LPI/WBES survey discussed above. These are pure survey data designed to reflect actual experience on the ground, and not "in principle" official times. Indeed, the results in column 7 of Table 2 strikingly reflect the difference between the potential endogeneity of this experience measure, and the "in principle" DB measure: the coefficient on time is much smaller than for the DB data, and is not statistically significant. I interpret these results as providing

[6]Results based on the WBES data are available on request. They are generally similar to those using the WEF data, except when very small samples make the regressions uninformative.

some supporting evidence in favor of the exogeneity of DB trade time data with respect to corruption.

A second way in which the endogeneity issue arises is the argument that bureaucrats might set high trade times in order to be able to extract rents–a form of the optimal harassment problem examined by Kaufmann and Wei (1999). To deal with this possibility and the previous one, I use two instrumental variables strategies. Columns 3-6 of Table 2 present two-step GMM estimates.[7] As a first strategy, I instrument for trade time using DB data on the number of documents that must be completed in order to comply with border formalities. Since these administrative requirements are determined at a level of authority higher than that of an individual customs officer, it is less likely that they are subject to the harassment problem. Similarly, individual officials cannot set centralized paperwork requirements at a level designed to extract maximum bribes. To over-identify the model, I also include a measure of each country's land area, which impacts Doing Business trade times because they take account of internal transit.

First stage estimates in column 4 suggest that the instruments do a good job of explaining observed variation in trade time. The null hypothesis that the coefficients on the instruments are individually zero is rejected in each case at the 10% level or better, as is an F-test of the joint null hypothesis ($F^2_{105} = 26.78$, $p\left(F^2_{105}\right) = 0.00$). The configuration of coefficient signs is generally sensible, with both trade documents and internal land area impacting positively on trade time. In addition, the instruments appear to be valid in the sense of being uncorrelated with the main equation error term, since Hansen's J fails to reject the null ($\chi^2_1 = 0.522$, $p\left(\chi^2_1\right) = 0.470$).

Column 5 presents second stage results, which generally accord with the baseline. The coefficient on trade time is positive and statistically significant at the 1% level. Government effectiveness, and cultural tolerance of corruption both have the expected signs; the first of these coefficients is statistically significant at the 5% level, and the second is marginally significant at the 10% level ($p = 0.115$).

These instrumental variables results support the results in the rest of the paper, thereby suggesting that endogeneity would not appear to be a major issue in these data. Indeed, a Durbin-Wu-Hausman endogeneity test fails to reject the null ($\chi^2_1 = 1.840$, $p\left(\chi^2_1\right) = 0.175$). It could be objected, however, that in a

[7]The dependent variable is the same as in the OLS and Tobit regressions. The literature does not disclose an appropriate IV estimator for the ordered probit model.

thoroughly corrupt society, central bureaucrats might set the level of trade documentation so as to enable individual border officials to extract bribes. To deal with this possibility, I follow Djankov et al. (Forthcoming) and limit the sample to landlocked countries only. Since DB trade time data reflect the total time required to move goods from the factory to the most accessible port, they include transit through neighboring countries in the case of landlocked countries. Trade time in neighboring countries can therefore be a valid instrument for trade time in a landlocked country: the two should be strongly correlated because of the way in which the DB data are constructed, but it is very unlikely that bureaucrats or officials in the landlocked countries can determine times or procedures in neighboring countries.

Results from this second instrumental variables strategy appear in columns 5-6 of Table 2. Although they must be treated with caution due to the very small sample size involved, it is nonetheless striking that they remain remarkably close to the baseline. Trade time has a positive and statistically significant coefficient (5%), while government effectiveness has a negative and 5% significant coefficient. Cultural tolerance of corruption has a positive coefficient, but it is statistically insignificant. Voice and accountability has the only coefficient with an unexpected sign (positive), but it is statistically insignificant. In terms of instrument validity, the first stage regression shows that trade time in neighboring countries is positively and significantly correlated with trade time in landlocked countries: the first stage F-test is 21.57 ($p = 0.000$). Combined with a Durbin-Wu-Hausman endogeneity test that fails to reject the null ($\chi_1^2 = 0.002$, $p\left(\chi_1^2\right) = 0.962$), the closeness of these results to the baseline strongly suggests that the possible endogeneity of trade time with respect to corruption is not a serious problem in these data. It is important to stress, of course, that this is not a general result applying to all measures of trade time, but a highly specific one applying to the DB data only.

4.3 Other Robustness Checks

I subject the baseline model to a number of robustness checks to ensure that the above conclusions are not unduly sensitive to the way in which the model is specified. They cover four dimensions: inclusion of additional trade policy data (Table 3); use of alternative independent variable sets (Table 4); changes in the estimation sample (Table 5); and alternative estimation techniques (Table 6).

4.3.1 Additional Trade Policy Data

There is already a wealth of empirical evidence demonstrating that higher and more variable tariffs are associated with more prevalent corruption (Fisman and Wei, 2004; Dutt, 2008; Dutt and Traca, Forthcoming). Since tariffs are simply a discriminatory tax, it is not surprising that higher rates should be associated with more prevalent evasion behavior necessitating the payment of bribes to customs officials. Similarly, highly variable tariff rates provide an incentive for traders to seek the re-classification of goods according either to product type or origin, so as to benefit from a lower tax rate. Customs agents are in a position to provide this kind of service, but will require the payment of a bribe in order to do so. However, the model in Section 2 abstracts from tariffs and other trade costs to focus on the role of time.

Casual empiricism suggests that countries that are in general less open (i.e., those with higher tariff rates) will also tend to have slower border crossing times. Indeed, the correlation between DB trade time and simple average tariffs from TRAINS is 0.441. It is therefore important to exclude the possibility that the baseline results are really being driven by tariffs. To do this, I re-estimate the model using tariff data from TRAINS, as well as theory-consistent trade restrictiveness indices (OTRIs) from Kee et al. (2008) covering tariffs and non-tariff barriers.

Results in Table 3 show that the relationship between trade time and corruption is highly robust to the inclusion of additional trade policy measures: the coefficient on time remains positive and at least 5% significant in all regressions, and has a magnitude that is remarkably close to the baseline. Interestingly in light of previous work, results are very mixed in terms of the coefficients on the various trade policy variables. TRAINS tariffs (column 1) and the tariff-only OTRI (column 2) have the expected positive sign, but are statistically insignificant. The tariff and NTB OTRI (column 3) has an unexpected negative sign, but the coefficient is statistically insignificant. However, results in columns 4-5 suggest that the lack of significance of the trade policy coefficients may be an artifact of the data, perhaps linked to the difficulty of aggregating tariffs and NTBs across many thousands of product lines, or to the poor quality of data on NTBs and preferential tariff rates. Blunter measures of tariff rates, i.e. the percentage of tariffs that can be regarded as "peaks" under alternative UNCTAD definitions, have coefficients that are positive and statistically significant, in line with previous work (columns 4-5). The percentage of duty free lines in the national tariff schedule also carries the expected sign (negative), but the coefficient is statistically insignificant. Based on these results, I conclude that tariff rates are a possible alternative explanation for the prevalence of trade related corruption (see also Sequiera and Djankov, 2009), but that they are not driving the observed relationship between time and corruption: it is highly robust to the inclusion of other measures of trade policy in the model.

4.3.2 Alternative Independent Variable Sets

In addition to the possible role of trade policy discussed above, it is also important to exclude other factors that might be driving the association between trade time and corruption. First, I address the argument that the baseline results might simply be picking up an association between the general level of corruption in a country, and the general quality of its regulations. To exclude this possibility, I use a placebo strategy. In column 1 of Table 4, I re-estimate the baseline model using DB data on the time it takes to start a business in a given country in place of trade time. These data have been widely used in empirical work as a proxy for the general level of national regulatory burdens (e.g., Helpman et al, 2008). Whereas trade time in the baseline regression has a positive and 1% significant coefficient, startup time has a slightly positive but statistically insignificant coefficient ($prob = 0.303$). It therefore seems unlikely that the baseline results simply reflect a general correlation between regulatory quality and corruption, but rather contain specific information as to the relationship between trade time and trade-related corruption.

It could also be argued that a number of categories of excluded country characteristics might be driving the results. First, I consider economic characteristics. Column 2 of Table 4 includes aggregate GDP and GDP per capita, as proxies for country size (Azfar and Knack, 2003) and level of economic development (Treisman, 2000; Ades and Di Tella, 1999) respectively. Column 3 includes the share of trade in GDP, a common proxy for openness, to account for the constraining effects of international competition on corruption (Treisman, 2000; Sandholtz and Koetzle, 2000; Knack and Azfar, 2003). Column 7 includes the percentage of oil, minerals, and fuel in total exports, as a proxy for the importance of resource rents that might tend to promote corruption (Ades and Di Tella, 1999). I find that income level and openness are negatively associated with corruption prevalence, as expected, but that the coefficients are statistically insignificant. The coefficients on country size and the extent of resource rents are positive but statistically insignificant. In all cases, the coefficient on trade time remains positive, statistically significant, and close in magnitude to the baseline, which suggests that the key result is not being driven by omitted country-level economic characteristics.

Next, I consider institutional characteristics as another possible driving force behind both variables: it could be argued that better institutions lead to more efficient regulation (lower trade times) and reduced corruption prevalence. Column 5 of Table 4 includes colony dummies, capturing colonization by Britain, France, Spain, Portugal, and Russia (Treisman, 2000). Column 6 includes dummies for British, French, Socialist, and Scandinavian legal origins (Treisman, 2000). Column 7 includes dummies for majoritarian electoral rules and presidential regimes (Kunicova and Rose-Ackerman, 2005). Column 8 includes data on the percentage of the population in each country identifying themselves as belonging to a major religion (Buddhism, Hinduism, Islam, Judaism, Orthodox Christianity, Protestantism, and Roman Catholicism). In all cases, results remain very close to the baseline. In particular, the coefficient on trade time remains positive, statistically significant, and of relatively stable magnitude. Conditional on all of the other variables in the model, I find that countries colonized by France tend to have higher levels of corruption prevalence (marginally significant at the 5% level), but that colonization by other powers does not have any statistically significant impact. Scandinavian legal origins are strongly associated with lower levels of corruption (1% significant), but other legal origins do not have a statistically significant impact. Finally, a majoritarian electoral rule is associated with higher levels of corruption, while the opposite is true for presidential regimes; however, neither effect is statistically significant. The difference between these findings and previous results in the literature–in which British colonization and a common law legal system have, in particular, been associated with less prevalent corruption–can most likely be explained by the use here of data on cultural and institutional characteristics that theory suggests should directly affect corruption prevalence. Past work on colonization and legal origins has tended to use those dummy variables as a means of capturing general institutional characteristics, so it should not be surprising that they essentially lose statistical significance once explicit measures of institutional development are included.

As a final robustness check with respect to omitted country characteristics, the last column of Table 4 includes continent dummies to account for the possibility of neighborhood effects. It could be argued, for example, that countries that are geographically close to one another might tend to have similar economic institutions and approaches to trade facilitation. However, results are once more close to the baseline.

In this section, I have controlled for country-level economic and institutional determinants of corruption, based on variable sets used extensively in the existing literature. Taking these results together shows the association between trade time and trade-related corruption prevalence to be highly robust. It is unlikely to be driven to a significant degree by omitted country characteristics.

4.3.3 Alternative Country Samples

The baseline estimates include in their sample all countries for which the relevant data are available. However, there are two dimensions in which sample selection might be an issue. The first stems from the possibility that there are unobservable characteristics of some country groups that could drive the apparent relationship between trade time and corruption, or interact with some of the explanatory variables. For instance, there are suggestions in the literature that the relationship between corruption and economic activity might be fundamentally different in Asia than in other regions (e.g., Rock and Bonnett, 2004), which would suggest that the model coefficients might be different from one geographical area to another. To exclude this possibility in so far as possible, I re-estimate the model excluding four groups of countries that might be thought to have particular characteristics relevant to the relationship being tested. Results are in Table 5.

Column 1 excludes high income countries from the sample, on the basis that governance institutions are particularly strong, and economic regulations particularly developed, in these countries. Column 2 excludes high and upper middle income countries, on the same basis. Column 3 excludes low income countries due to their presumptively weak institutions and comparatively poor governance. (All groups are defined according to the World Bank's country classification.) Column 4 excludes African countries from the sample, as institutions are particularly weak in some cases, and corruption is known to be endemic in some parts of the continent. Column 5 excludes Asian countries, for the reason mentioned above.

In all five cases, the coefficient on trade time remains positive, statistically significant at the 10% level or better, and of comparable magnitude to the baseline. The only departures from the baseline results are in Columns 1 and 5 (high income countries excluded; Asian countries excluded), where cultural acceptance of corruption has an unexpected negative sign, and voice and accountability has an unexpected positive sign. However, neither coefficient is statistically significant. Interestingly, the coefficient on voice and accountability becomes 5% significant once African countries are excluded from the sample, suggesting that its role as a constraint on corrupt behavior may only be relevant for countries with particular institutional configurations.

The second dimension of sample selection that could be important for these results is the argument that the collection of corruption perceptions data such as the WEF index tends to focus on countries that are of particular commercial interest to multinational firms, since the WEF survey is based on executive opinions (cf. Azfar and Knack, 2003). To address this possibility, I use a Heckman sample selection model. In these estimates, I drop the Fisman and Miguel (2006) proxy for cultural acceptance of corruption since its availability represents the most serious constraint on the estimation sample. (Re-estimating the baseline model without that variable produces results that are almost identical, using 115 observations rather than 111.) To over-identify the Heckman model, I use two data sources. In columns 1-2 of Table 6, I use a dummy variable equal to unity if a country is included in the World Bank's LPI sample as a proxy for the ease of obtaining reliable trade and customs data in particular countries; this variable should be correlated with the presence or absence of a country from the WEF sample, but should not otherwise influence observed corruption prevalence. In columns 3-4, I use a dummy variable equal to unity if a country has a United Nations Mission in New York City, based on the Fisman and Miguel (2006) data, as a proxy for the ability of countries to have some minimum level of involvement in the international system. Again, this variable should be correlated with inclusion in the WEF sample–since it suggests that a country is on the international "radar screen"–but should not otherwise affect corruption prevalence.

Results in columns 1-4 of Table 6 suggest that the excluded variables–inclusion in the LPI sample and possession of a UN Mission in New York City–do a good job of explaining inclusion in the WEF sample: both are 1% significant in their respective first stage (selection) regressions. In terms of the second stage (outcome) regressions, results are in line with the baseline in terms of sign, but only government effectiveness is statistically significant (1%). The coefficient on trade time is smaller than in the OLS baseline (Table 6 column 6), and is statistically insignificant; however, the hypothesis that the Heckman coefficients are equal to the OLS baseline coefficient cannot be rejected at the 5% level in either case. Moreover, the estimated correlation between the error terms in the selection and outcome equations ($\widehat{\rho}$)

is not statistically different from zero in either Heckman model. This last result strongly suggests that sample selection is not a major problem in these data, and that it is appropriate to rely on the baseline results.

4.3.4 Alternative Estimators

A final dimension of robustness relates to the choice of estimator. First, I examine whether the effect of trade time on corruption is non-linear, as suggested by Dutt and Traca (Forthcoming) in the case of tariffs. Column 5 of Table 6 therefore includes trade time in levels and squares. Interestingly, I find some evidence that nonlinear effects may indeed be present: both coefficients are statistically significant at the 5% level or better. The pattern of coefficients is suggestive of an inverted U relationship between trade time and corruption. In this dataset, the overall impact of trade time on corruption is always positive, and only a small handful of observations fall on the downward sloping part of the inverted U. The effect of trade time on corruption is strongest in Kenya, which has an average trade time of 53.5 days and a WEF corruption score of 3 out of 7.

All results using WEF data have relied on an ordered probit estimator, and thus on the assumption that the error term e_i is normally distributed. Another possibility is that the error term is log-normally distributed, in which case an ordered logit would be superior. There is no a priori reason to prefer one assumption over the other, so I re-estimate the model as an ordered logit. Results in column 5 of Table 6 are very close to the baseline in all respects, which suggests that little turns on the assumption that is made regarding the distribution of the error term.

An alternative approach to estimation using the WEF data is to treat them as continuous, rather than categorical. Since the data point for each country represents the average of responses across a number of survey participants, results frequently fall between categories, and the analysis thus far has relied on rounding to sort these averages into groups that reflect the original WEF categories. In columns 6-8 of Table 6, I therefore re-estimate the model using the raw WEF data in logarithms, i.e. not rounded to the nearest integer. The first set of estimation results uses OLS, while the second and third use a Tobit estimator to reflect the existence of a lower bound on the dependent variable at $\ln(1) = 0$ and an upper bound at $\ln(7)$ (column 7), or at the observed minimum and maximum in the data (column 8). The coefficient on trade time is positive and statistically significant in all cases. Government effectiveness has a negative and statistically significant coefficient, and cultural tolerance of corruption has a positive coefficient that is statistically significant in all three cases. Voice and accountability is not statistically significant in either case, and carries an unexpected positive coefficient in the OLS and second Tobit regressions.

5 Gravity Regressions

The empirical results presented in Section 4 strongly suggest that, based on cross-country data, trade times are an important determinant of observed levels of trade-related corruption. Based on the theory set out in Section 2 and the Appendix, an alternative way of identifying that link is through bilateral trade data: the effect of time on trade flows depends on the level of corruption present in the trading environment, so the interaction of time and corruption prevalence should be a statistically significant determinant of bilateral trade flows. As a complement to the cross-country regression results, I therefore also estimate a standard gravity model, and test whether or not the interaction term is significant (cf. Dutt and Traca, Forthcoming).

Anderson and Van Wincoop (2003) develop a micro-founded gravity model, and I take up their specification here:

$$\begin{aligned} \ln\left(X_{ij}\right) &= f_i + f_j + (1-\sigma)\sum_{c=4}^{C} b_c \ln\left(control_{ij}^{c}\right) + \ldots && (4) \\ \ldots &+ (1-\sigma)\left[b_1 \ln\left(time_{ij}\right) + b_2 \ln\left(corr_{ij}\right) + b_3 \ln\left(time_{ij}\right) \times \ln\left(corr_{ij}\right)\right] + e_{ij} && (5) \end{aligned}$$

The dependent variable X_{ij} is aggregate exports from country i to country j.[8] The CES elasticity of substitution among varieties within a sector is σ. The square brackets contain the trade costs function, which depends on trade time for both countries ($time_{ij}$), the level of corruption in both countries ($corr_{ij}$), and the interaction between the two. A set of C control variables is also included, to take account of standard geographical and historical factors that have been found to influence trade costs in the gravity

[8] In future work, I intend to complement these results with gravity models using sectoral trade data so as to account for differences in time sensitivity across different classes of goods (Hummels, 2001; Djankov et al., Forthcoming).

literature. Distance (as a proxy for transport costs) is the most common example. The e_{ij} term is a random shock satisfying the usual assumptions.

Exporter and importer fixed effects are specified as $f_i = \ln(Y_i) + (1-\sigma)\ln\Pi_i$ and $f_j = \ln\left(E_j\right) + (1-\sigma)\ln P_j$, where Y_i is total value added in the exporter, and E_j is total expenditure in the importer. The Π_i and P_j terms capture respectively outward and inward multilateral resistance. Outward multilateral resistance $(\Pi_i)^{1-\sigma} = \sum_{j=1}^{N} \left\{\frac{[]}{P_j}\right\}^{1-\sigma} \frac{E_j}{Y}$ is a weighted average of trade costs across all of country i's export markets, and inward multilateral resistance $\left(P_j\right)^{1-\sigma} = \sum_{i=1}^{N} \left\{\frac{[]}{\Pi_i}\right\}^{1-\sigma} \frac{Y_i}{Y}$ is a weighted average of trade costs across all of country j's suppliers.[9] These terms capture the fact that it is bilateral trade costs relative to the overall level of trade costs that matter for bilateral trade flows. Despite their complexity, an appropriate fixed effects configuration makes it possible to obtain consistent estimates of the parameters of interest using OLS. An additional advantage of this approach is that the importer fixed effects account for a wide range of trade barriers such as MFN tariffs, and many NTBs that apply to all exporters equally.

Unfortunately, neither trade time nor corruption data are available on a bilaterally disaggregated basis. Only country-specific measures are available, but they cannot be included directly in the gravity model because of collinearity with the importer and exporter fixed effects. I therefore assume that trade time and corruption in the exporting and importing countries both enter the trade costs function symmetrically, i.e. with the same coefficient for both countries in each case: $\ln\left(time_{ij}\right) = \ln\left(time_i \times time_j\right)$, and $\ln\left(corr_{ij}\right) = \ln\left(corr_i \times corr_j\right)$.[10].

I estimate the above model using WITS-Comtrade bilateral trade data combined with the same WEF corruption data and DB trade time data used above. As historical and geographical controls, I use international distance, a dummy variable identifying dyads with a past colonial link, another dummy identifying dyads with a common historical colonizer, a dummy for geographical contiguity, and a dummy for countries that share the same official language. All historical and geographical controls are taken from the CEPII distance dataset (Mayer and Zignago, 2006).

[9] The terms in square brackets refer to the trade costs function, which is in square brackets in equation (4).

[10] In future versions of this paper, I intend to check the robustness of these gravity model results to possible concerns that trade time and corruption might be endogenous to trade flows. At this stage, I treat these variables as exogenous. Djankov et al. (Forthcoming) show that this is a highly plausible assumption for the DB trade time data, while the leading contributions in the trade and corruption literature treat the corruption level as exogenous to bilateral trade (Anderson and Marcouiller, 2002; Dutt and Traca, Forthcoming).

Column 1 of Table 7 presents a gravity model including trade time and controls only, for purposes of comparison with the results of Djankov et al. (Forthcoming). As in that paper, I find a negative and statistically significant impact of trade time on bilateral trade. However, the estimated elasticity in column 1 (-2) is considerably greater in absolute value than the magnitude reported by Djankov et al. (Forthcoming) (-0.5). Part of the difference is due to methodology and data: I use a fixed effects approach to capture multilateral resistance, whereas Djankov et al. (Forthcoming) estimate using first differences; as a consequence, I measure time bilaterally, whereas they only include time data for exporters. The effectiveness of their model in accounting for multilateral resistance depends crucially on the unverifiable assumption that similar countries (i.e., members of the same regional agreement and income group) face similar overall levels of trade costs. Fixed effects, on the other hand, necessarily capture multilateral resistance in the dimensions implied by theory. In addition to these methodological issues, it also appears that the time data have been substantially revised by the World Bank: the estimation sample used here covers 152 exporters, whereas Djankov et al. (Forthcoming) only had data on all variables for 98 exporters. The data points for individual countries have been revised in a few cases too, sometimes substantially.

Column 2 introduces WEF corruption data into the gravity model. In line with past results (e.g., Anderson and Marcouiller, 2002), I find that higher levels of corruption are associated with lower levels of bilateral trade. The effect is quantitatively important, with an elasticity of -2, and is statistically significant at the 1% level. Moreover, in column 3 I find that the interaction between corruption and trade time has a negative coefficient that is statistically significant at the 10% level. Thus, the bilateral trade data tend to suggest that corruption and trade time do not have strictly independent effects on trade, but instead interact to produce an overall negative impact. This finding is directly in line with predictions from the theoretical model presented in Section 2 and the Appendix, and also reflects results reported by Dutt and Traca (Forthcoming) in the case of tariffs. In terms of quantitative importance, a 10% increase in trade time is associated with a 14.488% fall in bilateral trade in a corruption free country ($corrupt_i = 1$), but with a 15.252% fall in a country with rampant corruption ($corrupt_i = 7$). Although the difference between the two elasticities is relatively small–of the order of 5%–it is nonetheless economically significant.

Finally, columns 4-5 of Table 7 re-estimate the interaction model using a Heckman sample selection estimator. I assume that missing Comtrade data are indicative of zero trade flows between the relevant country pairs.[11] Helpman et al. (2008) provide a theoretical basis for using this type of approach to estimate a gravity model when the trade matrix contains a substantial number of zero entries. I use the standard Heckman correction to account for firm self-selection into foreign markets, but I do not apply the additional correction they propose to deal with firm heterogeneity. As in Helpman et al. (2008), I over-identify the model by including DB data on the costs of starting a firm–a proxy for the fixed costs of market entry–in the selection (trade propensity) equation, but not in the outcome (trade flow) equation.

In this case, the Heckman model does not produce substantially different results from OLS. The outcome equation in column 4 includes negative and statistically significant coefficients on trade time, corruption, and their interaction. The same is true of the trade time (statistically insignificant) and interaction coefficients (1% significant) in the selection (probit) equation. However, the corruption coefficient in that equation is positive and statistically significant. The reasons behind that result are deserving of additional analysis, but for present purposes it suffices to highlight that regardless of the sign of the corruption term, the interaction remains negative, and thus consistent with the cross-country regression results above. In any case, the Heckman results should be regarded as a robustness check only: the correlation between the error terms in the selection and outcome equations is very weak and statistically insignificant ($\widehat{\rho} = -0.018$, $\chi_1^2 = 0.87$, $p\left(\chi_1^2\right) = 0.352$), which suggests that sample selection is not a major problem in these data.

6 Conclusion

This paper has provided some of the first empirical evidence on the importance of trade time as a determinant of trade-related corruption. I find that longer trade times are significantly associated with higher levels of trade-related corruption, and that this association is robust to the use of a wide variety of independent variables, country samples, and estimation methods. The baseline results are obtained using a corruption perception index, but they also hold up using survey data on the percentage of firms required to make a gift in connection with trade transactions. In terms of magnitude, this paper's results are suggestive of a modest but significant impact of trade time on corruption, and of those factors together on

[11] Just over 10% of the sample (1352 observations) falls into this category.

bilateral trade. As an approximation, OLS estimates of the baseline cross-country regression suggest that increasing trade time by one day in the median country (27.5 days) is associated with an increase in its WEF corruption score of about 1%. From the estimated parameters of the gravity model, it can be seen that a a 10% increase in trade time is associated with a 14.488% fall in bilateral trade in a corruption free country, but with a 15.252% fall in a country with rampant corruption; this represents a difference of around 5% in the two elasticities.

On a policy level, these results are interesting for at least two reasons. First, they expand the range of policy instruments available for anti-corruption efforts to include trade facilitation in its broadest sense, namely measures that reduce the time and cost of moving goods across borders. This link is particularly important in weak institutional environments, since many alternative policies aimed at controlling corruption at the border, such as improved detection and enforcement or investments in human capital and training, are extremely difficult to implement over the short- to medium-term. Indeed, it is doubtful whether countries in which such reforms can be implemented quickly and effectively should be considered as having weak institutions in the first place. Experience suggests that reforms to border administration and trade facilitation can be successfully implemented through a staged process that is feasible even in comparatively weak institutional environments (e.g., McLinden, 2006). Improved trade facilitation can therefore be a useful short-term step in helping control corruption at the border

Second, international agencies involved in providing financing and technical assistance to improve trade facilitation in client countries are increasingly required to face up to the challenges posed by corruption in those countries. As an example, the controversy in 2006-2007 over the World Bank's role in dealing with governance and corruption issues is illustrative of an important tension (see World Bank, 2007). On the one hand, multilateral agencies can experience pressure from donor countries and international civil society groups to cut back on aid in poorly governed and/or corrupt environments. But there is also a strong argument that, at least in some cases, on-going engagement and investment can be a way of helping bring about governance reforms over the longer term. This paper's results tend to support a limited version of that point of view: improved trade facilitation requires extensive financial support and technical assistance, but it is a clear example of a situation in which foreign aid can be targeted in such a way as to reduce the importance of private rents and the incidence of corruption (cf. Rose-Ackerman, 1997).

In terms of future research in this area, there are a number of additional directions that could usefully be explored. One interesting and important question relates to the firm-level determinants of corruption. Svensson (2003) uses a survey of Ugandan firms to show that not all agents in the same market report having to pay bribes, and that among bribe payers there is considerable variation in the amount paid. Casual empiricism using similar data available across multiple countries through the WBES suggests that this finding is by no means unique to the data considered by Svensson (2003), and applies equally well to trade-related corruption. Explaining this variation remains key to developing a better understanding of the way in which incentives structure corrupt behavior on a micro-level.

Clearly, the phenomenon of speed money is not limited to international trade transactions, but can also apply to other situations in which time-sensitive individuals seek access to government services. Obtaining business permits, dealing with fiscal authorities, and having utilities connected are examples of other areas in which corrupt payments for faster service might be an issue. Data are available from sources such as DB and WBES on the extent of these problems in different countries, and the way in which firms respond to them. It would be instructive for future work to replicate the results from this paper using data for other types of government activities.

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Appendix: A Theoretical Model of Speed Money

As in Evans and Harrigan (2005), the model's timing is as follows:

1. Customs agents decide whether or not to be corrupt, and choose the "gift" required in order to secure quick passage of goods through customs.

2. Firms decide how much to produce.

3. Period 1 demand is realized, and firms decide how much to sell in period 1. Unsold production is carried over costlessly to period 2.

4. Fast firms produce again. Slow firms do not.

5. Period 2 demand is realized, and firms decide how much to sell in period 2. Unsold production is discarded.

The Slow Firm's Problem

The slow firm is a monopolist with inverse demand as in Evans and Harrigan (2005):

$$p = a - bs \tag{6}$$

where p is price, s is sales, and a and b are parameters. Demand in each period is uncertain, with $\{a_1, a_2\} \in \{a_H, a_L\}$ where $a_H > a_L$, and $E[a] = \overline{a}$. Since the setup is identical, the slow firm's profit-maximizing production and sales plan is exactly as in Evans and Harrigan (2005):

$$s_1^S = s_2^S \frac{q^S}{2} + \frac{a_1 - \overline{a}}{4b};\ s_2^S = \frac{q^S}{2} - \frac{a_1 - \overline{a}}{4b} \tag{7}$$

$$q^S = \frac{\overline{a} - 1}{b} \tag{8}$$

where q is the total quantity produced, and subscripts indicate time periods.[12] Labor is perfectly homogeneous and mobile between sectors, and its supply is perfectly elastic at the prevailing wage rate, which I normalize to unity.

Evans and Harrigan (2005) show that ex ante expected profits for the slow firm are:

$$E\left[\pi^S\right] = s_1^S\left(\overline{a} - bs_1^S\right) + s_2^S\left(\overline{a} - bs_2^S\right) - q^S \equiv \frac{4\overline{a}^2 - 4 + V(a)}{8b} - \frac{\overline{a} - 1}{b} \tag{9}$$

where $V(a) = \rho a_H^2 + (1-\rho) a_L^2 - \overline{a}^2$ is the variance of the demand parameter a.

The Fast Firm's Problem

The fast firm is also a monopolist, with inverse demand function identical to the slow firm's. The total gift inclusive cost of producing and shipping one unit of output is $1 + \gamma g$, where γ is the proportion of customs agents who are corrupt, and g is the amount of the gift that must be paid for fast service. The fast firm's optimal production and sale plan closely follows the equivalent set of equations in Evans and

[12]See the unpublished appendix to Evans and Harrigan (2005) for details as to the conditions under which this type of model produces a meaningful equilibrium. Source: http://www.e-aer.org/data/mar05_app_evans.pdf.

Harrigan (2005):

$$s_1^F = s_2^F \frac{a_1 - 1 - \gamma g}{2b};\; s_2^F = \frac{\overline{a} - 1 - \gamma g}{2b} \tag{10}$$

$$q_1^F = q_2^F \frac{a_H - 1 - \gamma g}{2b};\; q_2^F = \frac{\overline{a} - 1 - \gamma g}{2b} - \left(q_1^F - s_1^F\right) \tag{11}$$

The fast firm takes corruption prevalence γ and the amount of the gift g as given, although they are in fact chosen endogenously by optimizing customs agents (see below).

Again, ex ante expected profits for the fast firm are very close to the similar expressions in Evans and Harrigan (2005):

$$E\left[\pi^F\right] = s_1^F\left(\overline{a} - bs_1^F\right) + s_2^F\left(\overline{a} - bs_2^F\right) - \left(q_1^F + q_2^F\right)(1+\gamma g)$$
$$\equiv \frac{4\overline{a}^2 - 4(1+\gamma g)^2 + 2V(a)}{8b} - \frac{\overline{a}(1+\gamma g) - (1+\gamma g)^2}{b} \tag{12}$$

In the absence of corruption ($\gamma = 0$ or $g = 0$), the fast firm would have higher ex ante expected profits than the slow firm, since from equations (9) and (12):

$$E\left[\pi^F\right] - E\left[\pi^S\right] = \frac{V(a)}{8b} > 0 \tag{13}$$

The Customs Agents' Problem

Customs agents can be of two types: honest (no acceptance of gifts), or corrupt (acceptance of gifts). An honest customs agent earns the economy-wide wage (1) with certainty each period. In addition, she earns an "honesty bonus" h, under the assumption that agents gain some kind of subjective satisfaction from following rules. In the interests of analytical tractability, I assume that the honesty bonus is drawn from a uniform distribution with cumulative distribution function $F(h) = \frac{h}{\overline{h}}$, and support $[0, \overline{h}]$.

By contrast, a corrupt customs agent earns the economy-wide wage plus the amount of any gift g extracted from traders. However, corrupt agents face a probability δ of detection. If an agent is found to be corrupt, he loses his job and receives an income of zero.

In equilibrium, utility maximizing customs agents equalize the returns from corruption and honesty such that:

$$1 + h = (1-\delta)(1+g) \tag{14}$$

Define h^* as the minimum honesty bonus required for a customs agent to remain honest for given g and δ, such that agents with $h \geq h^*$ are honest, and those with $h < h^*$ are corrupt. It follows immediately from above that:

$$h^* = g - \delta - \delta g \tag{15}$$

Define γ as the proportion of customs officers who are corrupt. Thus, $\gamma = P(h < h^*) = F(h^*) = \frac{h^*}{\overline{h}}$, where the last equality follows from the distributional assumption for the honesty bonus made above. Substituting for h^* gives:

$$\gamma = \frac{g - \delta - \delta g}{\overline{h}} \tag{16}$$

Ignoring possible indirect effects, it is obvious from inspection that a higher probability of detection tends to reduce the proportion of corrupt officials ($\frac{\partial\gamma}{\partial\delta} = -\frac{1+g}{\overline{h}} < 0$). A higher level of gifts has the opposite effect, however, since $\frac{\partial\gamma}{\partial g} = \frac{1-\delta}{\overline{h}} > 0$. Finally, an increase the average level of the honesty bonus–which could be interpreted as indicative of a culture of honesty–tends to reduce the proportion of corrupt officials ($\frac{\partial\gamma}{\partial\overline{h}/2} = -\frac{2(g-\delta-\delta g)}{\overline{h}^2} > 0$).

In equilibrium, corrupt customs officers cannot require a gift g in excess of the difference in ex ante expected profits between the fast and slow firms. To simplify the problem, I assume that customs officers have full bargaining power, and thus that they can extract the full difference in ex ante expected profits as a gift. This approach means that I can solve the model by finding a gift g^* that equalizes expected ex ante profits between the two firms. Thus:

$$\frac{4\overline{a}^2 - 4(1+\gamma g^*)^2 + 2V(a)}{8b} - \frac{\overline{a}(1+\gamma g^*) - (1+\gamma g^*)^2}{b} = \frac{4\overline{a}^2 - 4 + V(a)}{8b} - \frac{\overline{a}-1}{b} \tag{17}$$

First, I solve for $(1+\gamma g^*)$ and retain only the solution that is less than $\overline{a}$ (expected total demand):

$$1+\gamma g^* = \overline{a} - \frac{1}{2}\sqrt{8\overline{a}^2 - 12\overline{a} - V(a) + 4} \tag{18}$$

Now I substitute for γ using equation (16) and solve for g^*, retaining only the positive root:

$$\frac{g^{*2} - \delta g^* - \delta g^{*2}}{\overline{h}} = \overline{a} - \frac{1}{2}\sqrt{8\overline{a}^2 - 12\overline{a} - V(a) + 4} - 1 \tag{19}$$

$$g^* = -\frac{1}{2(\delta-1)} \times \left[\delta + \left\{d^2 + 4d\overline{h} + 4\overline{a}\overline{h} + 2d\overline{h}\left(8\overline{a}^2 - 12\overline{a} - V(a) + 4\right)^{\frac{1}{2}} - 2\overline{h}\left(8\overline{a}^2 - 12\overline{a} - V(a) + 4\right)^{\frac{1}{2}} - 4\overline{a}d\overline{h} - 4\overline{h}\right\}^{\frac{1}{2}}\right] \tag{20}$$

Provided that demand a has a mean $\overline{a}$ sufficiently large relative to its variance $V(a)$ and the other parameters, the equilibrium gift g^* must be positive. Although the solution itself and comparative statics based on it are difficult to interpret in detail, that same condition ensures that it is at least possible to draw conclusions as to the signs of two important partial derivatives:

$$\frac{\partial g^*}{\partial V(a)} = \frac{1}{4}\overline{h}\left(8\overline{a}^2 - 12\overline{a} - V(a) + 4\right)^{-\frac{1}{2}} \times \left(d^2 + 4d\overline{h} + 4\overline{a}\overline{h} + 2d\overline{h}\left(8\overline{a}^2 - 12\overline{a} - V(a) + 4\right)^{\frac{1}{2}} - 2\overline{h}\left(8\overline{a}^2 - 12\overline{a} - V(a) + 4\right)^{\frac{1}{2}} - 4\overline{a}d\overline{h} - 4\overline{h}\right)^{-\frac{1}{2}} > 0 \tag{21}$$

$$\frac{\partial g^*}{\partial\left(\frac{\bar{h}}{2}\right)} = -\left[\bar{h}\left(\delta-1\right)\right]^{-1} \times$$

$$\left[\delta + \left\{d^2+4d\bar{h}+4\bar{a}\bar{h}+2d\bar{h}\left(8\bar{a}^2-12\bar{a}-V\left(a\right)+4\right)^{\frac{1}{2}}-2\bar{h}\left(8\bar{a}^2-12\bar{a}-V\left(a\right)+4\right)^{\frac{1}{2}}-4\bar{a}d\bar{h}-4\bar{h}\right\}^{\frac{1}{2}}\right] > 0 \tag{22}$$

Thus, an increase in the variance of demand a is associated with higher bribe payments. This effect is highly intuitive, since the difference in ex ante expected profits between the fast and slow firms depends positively on the variance of demand, and that difference is captured in full by the corrupt customs agents through their capacity to extract gifts. Interestingly, an increase in the local culture of honesty is associated with a higher gift payment, which might seem surprising at first glance. However, this outcome reflects the fact that honesty is valued to some extent by all agents, and a higher average level means that a larger gift is required to overcome the extra utility gained from being honest. Comparing the effect of cultural honesty on the level of the gift versus the proportion of customs agents who are corrupt brings out an interesting tension: a higher average level of honesty bonus results in a lower proportion of corrupt officials (ignoring indirect effects), but those agents who are corrupt receive larger gifts.

Speed, Corruption, and Trade

The model can also say something about the effects that speed and corruption jointly have on trade flows. I treat sales as synonymous with trade in this section, since the model setup can equally well be interpreted as capturing domestic production and overseas sales with zero transport costs.

To see the effect of corruption on trade, I compare total expected sales of a fast firm in a corrupt environment (s^F) to those of a fast firm in a non-corrupt environment ($\tilde{s}^F$):

$$\tilde{s}^F = \tilde{s}_1^F + \tilde{s}_2^F = \frac{a_1+\bar{a}-2}{2b};\; s^F = s_1^F + s_2^F = \frac{a_1+\bar{a}-2\gamma g-2}{2b} \tag{23}$$

The reduction in sales due to corruption is therefore $\tilde{s}^F - s^F = \frac{\gamma g}{b} > 0$. However, the parameters γ and g–and thus the size of the corruption effect on trade–both depend on the difference in ex ante expected profits between fast and slow firms, and thus on the extent of the time delays that can be reduced or eliminated through corruption. The effect of corruption on trade therefore depends on its interaction with trade time.

Table 1: Data and sources.

Variable	Definition	Source
Accountability	Composite index of political voice and accountability.	WGI
Border	Equal to unity for countries with a common land border.	Mayer and Zignago (2006)
Colony	Equal to unity for colonization by the UK, France, Spain, Portugal, and Russia.	Mayer and Zignago (2006)
Common Colonizer	Equal to unity for two countries colonized by the same power.	Mayer and Zignago (2006)
Common Language	Equal to unity for countries with a common official language.	Mayer and Zignago (2006)
Continent	Equal to unity for countries located in Africa, Asia, Europe, America, and the Pacific.	Mayer and Zignago (2006)
Culture	Number of parking violations by NYC diplomats.	Fisman and Miguel (2006)
Distance	Great circle distance between capital cities.	Mayer and Zignago (2006)
Documents	Simple average of official export and import documents (number).	Doing Business
Domestic Tariff Peaks	National tariff lines greater than 3 times the average tariff (%).	TRAINS
Entry Cost	Cost of complying with official procedures for starting a business (% GNI per capita).	Doing Business
Entry Time	Time to comply with official procedures for starting a business (days).	Doing Business
Free Lines	National tariff lines set at zero ad valorem (%).	TRAINS
GDP	Aggregate gross domestic product (USD).	WDI
GDPPC	GDP per capita (USD).	WDI
Government Effectiveness	Composite index of government effectiveness.	WGI
International Tariff Peaks	National tariff lines greater than 15% ad valorem (%).	TRAINS
Land Area	Internal land area of a country.	Mayer and Zignago (2006)
Legal Origins	Equal to unity for British, French, Socialist, and Scandinavian legal origins.	
LPI Sample	Equal to unity for countries in the World Bank's Logistics Performance Index.	LPI
Majoritarian	Equal to unity for countries with a majoritarian electoral rule.	WBPID
Openness	(Exports + Imports)/GDP	WDI
OTRI	Overall trade restrictiveness index, tariffs only or tariffs and NTBs (% ad valorem equivalent).	Kee et al. (2008)
Presidential	Equal to unity for countries with a presidential regime.	WBPID
Religion	Percentage of the population identifying as Buddhist, Hindu, Muslim, Jewish, Orthodox, Protestant, or Roman Catholic.	World Values Survey
Resources	Minerals, ores, and metals in exports (% by value).	WDI
Tariff	Simple average applied tariff (% ad valorem).	TRAINS
Time	Simple average of official export and import times (days).	Doing Business
UN Mission	Equal to unity for countries with a UN Mission in New York.	Fisman and Miguel (2006)
WBES Corruption	Percentage of firms indicating a gift was given or expected in exchange for an import license.	WBES
WEF Corruption	Index of corruption prevalence in relation to import/export permits.	WEF

Table 2: Baseline cross-country regression results, and robustness checks to endogeneity.

	1	2	3	4	5	6	7
	WEF	WBES	IV/GMM 2nd	IV/GMM 1st	IV/GMM 2nd	IV/GMM 1st	Endog. Time
Time	0.676***	0.099**	0.455***		0.422**		0
	[0.219]	[0.042]	[0.176]		[0.207]		[0.232]
Govt. effect.	-2.957***	-0.02	-0.802**	-0.915***	-0.663**	-0.792**	-4.301***
	[0.645]	[0.069]	[0.338]	[0.165]	[0.303]	[0.316]	[0.781]
Account.	-0.25	-0.157**	0	-0.06	0.12	0.18	-0.17
	[0.425]	[0.078]	[0.124]	[0.133]	[0.279]	[0.312]	[0.462]
Culture	0.02	0.010**	0.02	0	0.01	-0.03	0.03
	[0.027]	[0.004]	[0.010]	[0.011]	[0.015]	[0.017]	[0.029]
Land area				0.034*			
				[0.020]			
Documents				0.817***			
				[0.118]			
Time (neighbors)						0.752***	
						[0.162]	
Observations	111	74	111	111	25	25	91
Wald / F test	92.09***	7.66***	54.76***	26.78***	10.04***	21.57***	81.97***
$R^2/Count\ R^2$	0.577	0.339	0.687	0.771	0.742	0.765	0.516
$Pseudo-R^2$	0.348						0.362
Hansen J			0.52				

1. All independent variables are in logarithms. In column 7, time is measured as the average of best export and import times reported by respondents to the WBES/LPI survey. Dependent variables are as follows: columns 1 and 7 use WEF corruption data in categories; column 2 uses WBES corruption data in percentage of firms; columns 3 and 5 use raw WEF corruption data in logarithms; and columns 4 and 6 use time in logarithms.

2. Robust standard errors are in square brackets. Statistical significance is indicated by * (10%), ** (5%), and *** (1%).

3. Estimation methods are as follows: columns 1 and 7 use ordered probit; column 2 uses OLS; and columns 3-6 use two-step GMM.

Table 3: Cross-country regression results using various indicators of trade policy.

	1	2	3	4	5	6
	Tariffs	OTRI (Tariffs)	OTRI (Tariffs+NTB)	% Intl. Peaks	% Dom. Peaks	% Free Lines
Time	0.684***	0.690***	0.668**	0.700***	0.651***	0.674***
	[0.220]	[0.248]	[0.276]	[0.219]	[0.218]	[0.220]
Govt. effect.	-2.808***	-2.916***	-3.129***	-2.721***	-3.131***	-2.759***
	[0.659]	[0.732]	[0.875]	[0.638]	[0.657]	[0.654]
Account.	-0.1	-0.1	-0.36	0.03	-0.24	-0.15
	[0.450]	[0.428]	[0.498]	[0.455]	[0.422]	[0.450]
Culture	0.02	0.03	0.05	0.02	0.02	0.02
	[0.027]	[0.029]	[0.034]	[0.028]	[0.027]	[0.027]
Trade policy	3.2	0.94	-2.05	2.006***	3.554**	-0.59
	[2.855]	[2.728]	[1.810]	[0.680]	[1.456]	[0.583]
Observations	111	96	77	111	111	111
Wald test	93.50***	70.10***	59.82***	91.15***	94.90***	92.64***
Count R^2	0.541	0.552	0.519	0.577	0.604	0.541
$Pseudo-R^2$	0.351	0.336	0.354	0.371	0.352	0.351

1. The dependent variable is WEF corruption data in categories. The trade policy variable is as indicated at the top of each column. The tariff rate, and both OTRI series are converted to logarithms; the data on peaks and free lines are already percentages.

2. Estimation is by ordered probit. Robust standard errors are in square brackets. Statistical significance is indicated by * (10%), ** (5%), and *** (1%).

Table 4: Cross-country regression results using alternative independent variable sets.

	1	2	3	4	5	6	7	8	9
	Placebo	Economy	Openness	Resources	Colonies	Legal Origins	Regimes	Religions	Continents
Entry time	0.17								
	[0.163]								
Time		0.632***	0.669***	0.876***	0.593***	0.476**	0.753***	1.103***	0.573**
		[0.229]	[0.223]	[0.270]	[0.219]	[0.234]	[0.291]	[0.396]	[0.230]
Govt. effect.	-3.674***	-2.708***	-2.940***	-3.052***	-3.566***	-3.392***	-3.380***	-3.634***	-3.737***
	[0.611]	[0.720]	[0.641]	[0.843]	[0.638]	[0.656]	[0.918]	[1.320]	[0.701]
Account.	-0.32	-0.29	-0.26	-0.28	0.15	-0.11	-0.32	0.06	0.53
	[0.436]	[0.439]	[0.425]	[0.535]	[0.455]	[0.428]	[0.821]	[0.733]	[0.566]
Culture	0.02	0.01	0.02	0.01	0.02	0.01	0.02	-0.01	0.01
	[0.029]	[0.028]	[0.027]	[0.032]	[0.027]	[0.029]	[0.031]	[0.044]	[0.030]
GDPPC		-0.16							
		[0.186]							
GDP		0.04							
		[0.067]							
Openness			-0.04						
			[0.224]						
Resources				0.31					
				[0.591]					
Observations	112	109	111	87	111	105	70	66	111
Wald test	87.48***	90.68***	92.54***	74.14***	111.89***	885.29***	71.12***	68.72***	96.15***
$Count\ R^2$	0.545	0.569	0.577	0.609	0.595	0.590	0.614	0.636	0.577
$Pseudo-R^2$	0.336	0.348	0.348	0.374	0.371	0.392	0.389	0.444	0.373

1. The dependent variable is WEF corruption data in categories. All independent variables are in logarithms, except for openness and resources (both in percentage).

2. Estimation is by ordered probit. Robust standard errors are in square brackets. Statistical significance is indicated by * (10%), ** (5%), and *** (1%).

3. Column 5 includes colonization dummies; column 6 includes legal origin dummies; column 7 includes dummies for a majoritarian electoral rule and a presidential regime; column 8 includes the percentage of the population belonging to each major religion; and column 9 includes continent dummies.

Table 5: Cross-country regression results using alternative country samples.

	1	2	3	4	5
	No High Income	No High/U-Middle Income	No Low Income	No Africa	No Asia
Time	0.431*	0.726**	0.677***	0.597**	0.771***
	[0.251]	[0.348]	[0.254]	[0.276]	[0.238]
Govt. effect.	-2.104***	-1.439**	-3.226***	-3.064***	-3.511***
	[0.643]	[0.696]	[0.758]	[0.757]	[0.824]
Account.	-0.36	-0.32	-0.25	-0.881**	0.6
	[0.417]	[0.472]	[0.426]	[0.436]	[0.593]
Culture	-0.01	0.07	0.01	0.02	0.01
	[0.035]	[0.044]	[0.031]	[0.030]	[0.031]
Observations	80	58	88	83	85
Wald test	41.86***	16.98***	70.93***	80.64***	67.66***
Count R^2	0.575	0.569	0.580	0.554	0.612
$Pseudo-R^2$	0.153	0.107	0.340	0.364	0.371

1. The dependent variable is WEF corruption data in categories. All independent variables are in logarithms.
2. Estimation is by ordered probit. Robust standard errors are in square brackets. Statistical significance is indicated by * (10%), ** (5%), and *** (1%).
3. Estimation sample in each column excludes the country group(s) indicated at the top of the column.

Table 6: Cross-country regression results using alternative estimators.

	1	2	3	4	5	6	7	8	9
	Heckman 2nd	Heckman 1st	Heckman 2nd	Heckman 1st	Non-Linear	Ordered Logit	OLS	Tobit	Tobit
Time	0.18	1.283***	0.13	0.45	3.185***	1.136***	0.232**	0.135*	0.229**
	[0.118]	[0.331]	[0.126]	[0.525]	[1.150]	[0.393]	[0.097]	[0.073]	[0.094]
Govt. effect.	-1.350***	2.433***	-1.428***	2.530***	-3.054***	-5.346***	-1.129***	-0.983***	-1.137***
	[0.262]	[0.618]	[0.248]	[0.645]	[0.652]	[1.266]	[0.211]	[0.172]	[0.207]
Account.	-0.03	0.874**	-0.13	1.162**	-0.3	-0.38	0	-0.06	0.01
	[0.143]	[0.370]	[0.163]	[0.523]	[0.412]	[0.804]	[0.131]	[0.102]	[0.129]
Culture					0.02	0.03	0.021**	0.014*	0.021**
					[0.029]	[0.050]	[0.010]	[0.008]	[0.010]
$\hat{\rho}$	-0.150		-0.630						
	[0.439]		[0.480]						
LPI sample		1.568***							
		[0.290]							
UN mission in NYC			2.507***						
			[0.636]						
Time^2					-0.400**				
					[0.179]				
Observations	162		162		111	111	111	111	111
Wald / F test	130.92***		141.67***		94.16***	76.19***	42.96***	46.30***	42.16***
$R^2/Count\,R^2$					0.586	0.568	0.703		
$Pseudo-R^2$					0.359	0.344		0.652	0.556

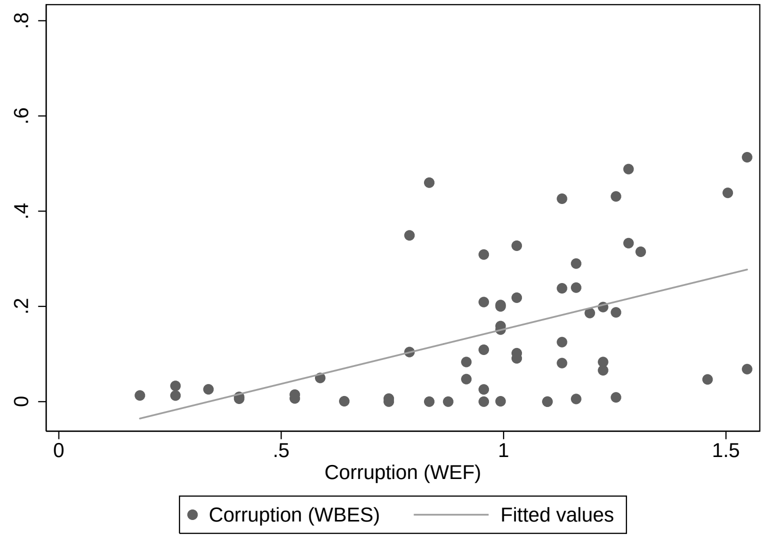
1. The dependent variable is raw WEF corruption data in logarithms, except for column 5 which is WEF corruption data in categories. All independent variables are in logarithms.

2. Estimation method is as indicated at the top of each column. Robust standard errors are in square brackets. Statistical significance is indicated by * (10%), ** (5%), and *** (1%).

Table 7: Gravity model regression results.

	1	2	3	4	5
	OLS	OLS	OLS	Heckman Outcome	Heckman Selection
Time	-2.019***		-1.449***	-1.446***	-0.3
	[0.092]		[0.093]	[0.094]	[0.227]
Corruption		-2.151***	-0.435***	-0.425***	1.248***
		[0.150]	[0.156]	[0.164]	[0.212]
Time*Corruption			-0.039*	-0.040*	-0.181***
			[0.023]	[0.024]	[0.031]
Distance	-1.480***	-1.509***	-1.403***	-1.435***	0.309***
	[0.032]	[0.034]	[0.034]	[0.034]	[0.041]
Border	0.763***	0.575***	0.779***	0.718***	2.430***
	[0.151]	[0.175]	[0.175]	[0.174]	[0.486]
Common Language	0.833***	0.614***	0.722***	0.730***	1.234***
	[0.069]	[0.078]	[0.084]	[0.084]	[0.116]
Common Colonizer	1.142***	1.084***	1.201***	1.209***	0.395***
	[0.098]	[0.110]	[0.128]	[0.126]	[0.124]
Colony	0.827***	0.902***	0.732***	0.722***	5.970***
	[0.134]	[0.147]	[0.143]	[0.143]	[0.305]
$\widehat{\rho}$				-0.018	
				[0.019]	
Entry Cost					-0.200***
					[0.070]
Observations	14,991	12,278	10,504	11,856	11,856
Wald / F test	163.83***	157.60***	152.33***	31754.79***	
R^2	0.772	0.784	0.796		

Figure 1: Corruption data - WEF (perceptions; in logarithms) vs. WBES (% of firms reporting a "gift" in relation to an import license).



1. One outlier (Chile) is excluded.

Figure 2: DB import time data vs. LPI/WBES import time data (median), in logarithms.

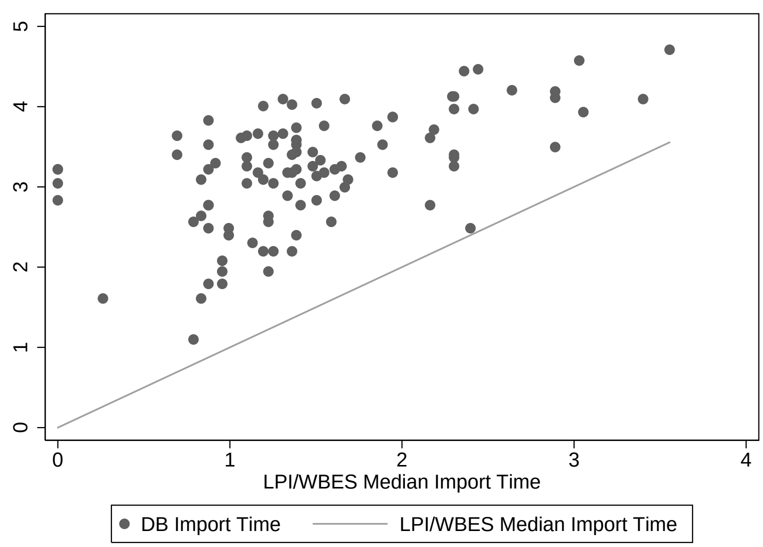


Figure 3: Non-parametric (Lowess) regression of corruption on trade time (both in logarithms).

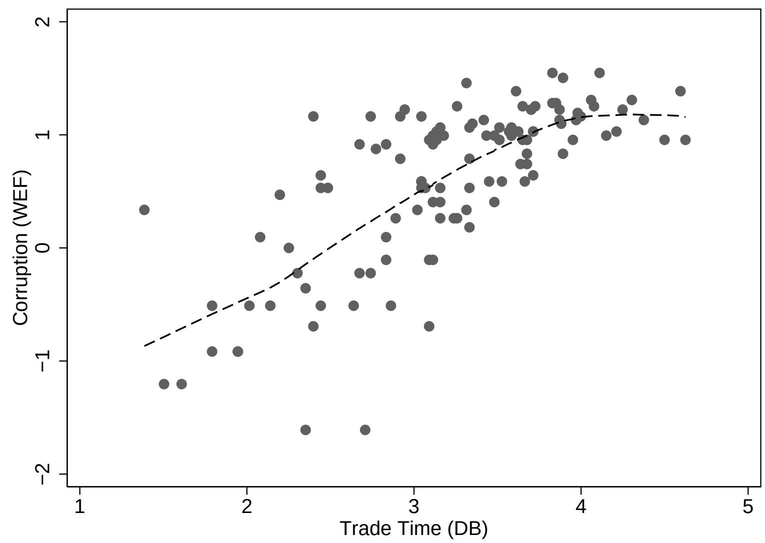


Figure 4: Non-parametric (Lowess) regression of corruption on government effectiveness (both in logarithms).

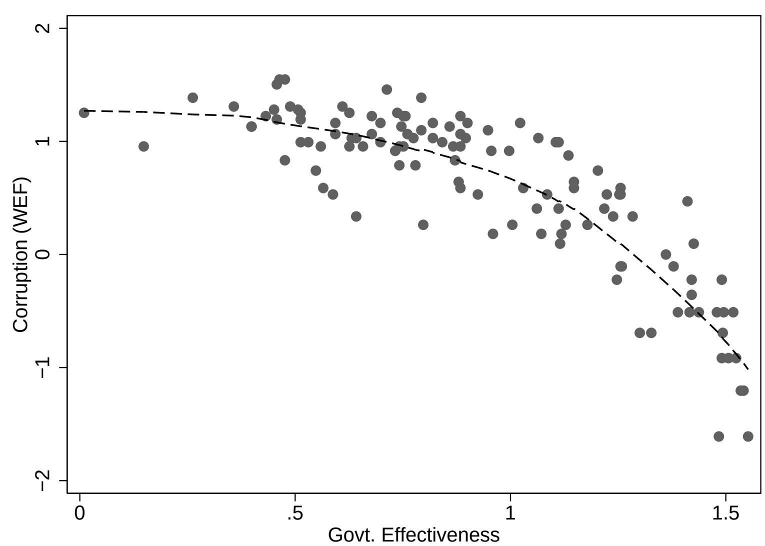


Figure 5: Non-parametric (Lowess) regression of corruption on voice and accountability (both in logarithms).

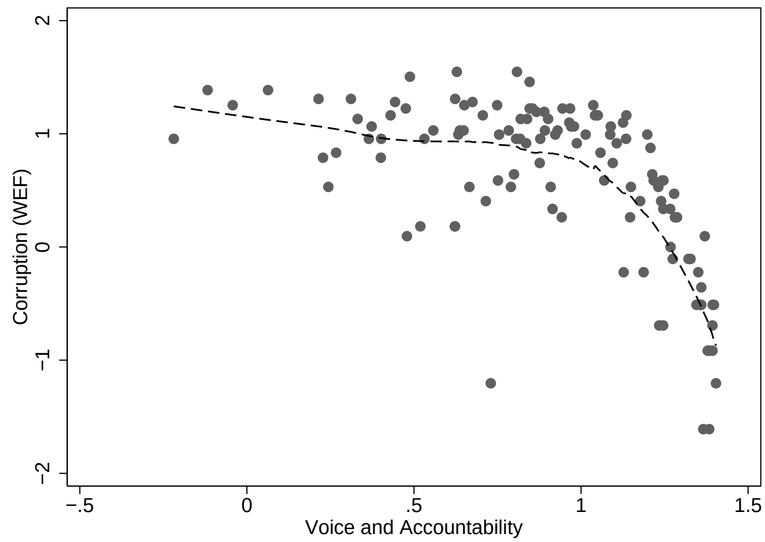
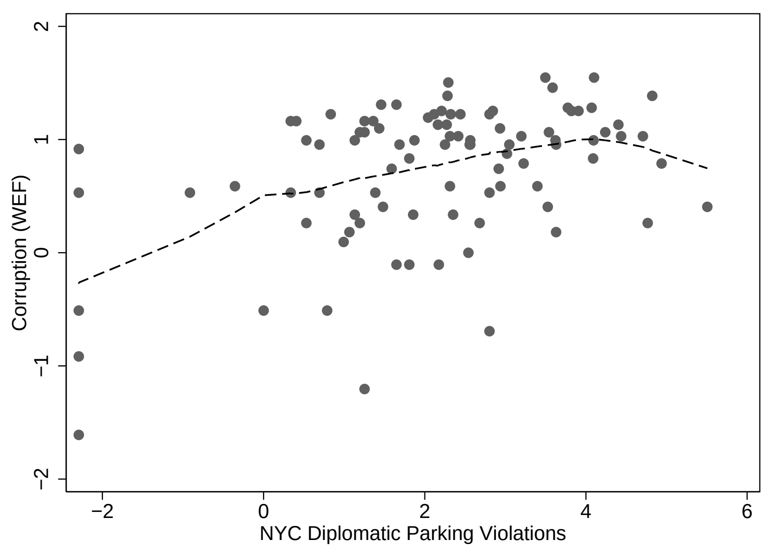
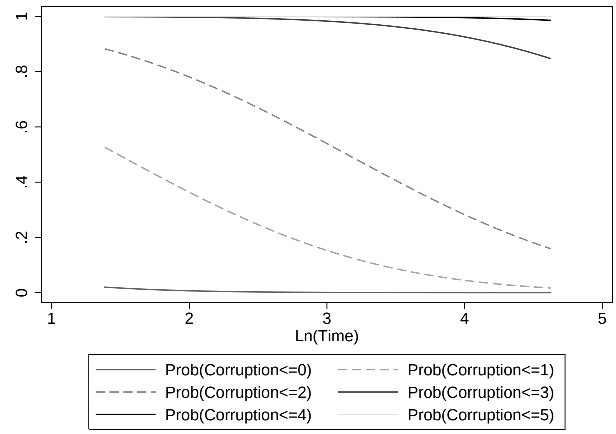


Figure 6: Non-parametric (Lowess) regression of corruption on parking infringements by New York City based diplomats (both in logarithms).



1. Only countries with a strictly positive number of parking violations are included. This drops 20 observations from the dataset.

Figure 7: Predicted cumulative probabilities - corruption vs. time.

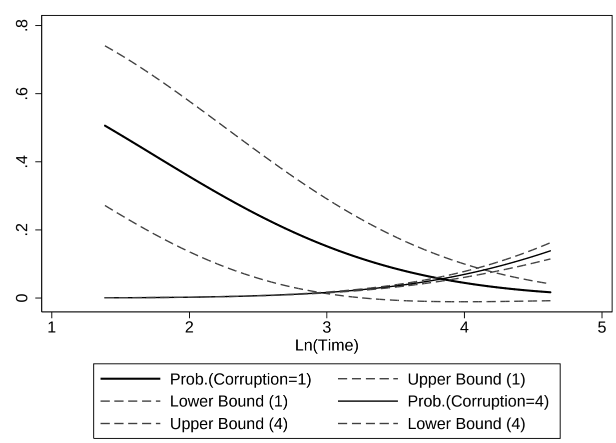


1. Predicted cumulative probabilities computed at 100 equidistant points between the minimum and maximum values of the natural logarithm of time.

2. All other variables are held constant at their median values.

3. Software due to Long and Freese (2005).

Figure 8: Predicted probabilities - corruption vs. time.



1. Predicted probabilities for corruption index scores of one and four (solid lines) computed at 100 equidistant points between the minimum and maximum values of the natural logarithm of trade time. Upper and lower bounds refer to the estimated 95% confidence interval.

2. All other variables are held constant at their median values.

3. Software due to Long and Freese (2005).