Bribe-Switching

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Abstract

The US Foreign Corrupt Practices Act (FCPA) prohibits the payment of bribes to foreign public officials. We uncover an unintended consequence – the *shadow* economies of the countries of these officials increase after FCPA enforcement. Our hypothesis is that if the FCPA successfully deters corruption in legal markets, corrupt officials can switch to taking bribes from *illegal* markets. In equilibrium, they enforce less against illegal producers, thereby increasing the size of illegal markets. We find that one case of FCPA enforcement alone increases the shadow economy by as much as 0.28 percentage points (pp), tree loss - an indicator of illegal logging, by 0.027 pp, and trade misinvoicing by 0.5 pp.

Keywords: corruption, bribery, shadow economy, illegal markets
JEL codes: D72, D73, K42, E26

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1 Introduction

The US Foreign Corrupt Practices Act (FCPA) is one of the most important pieces of anti-corruption legislation in the world. It prohibits US firms and persons, and foreign entities that have any dealings with the US from paying bribes to foreign public officials. It is the FCPA that enabled the US Department of Justice (DOJ) and the Securities and Exchange Commission (SEC) to prosecute Goldman Sachs for its involvement in the Malaysian 1MDB corruption scheme, and Petroleo Brasileiro SA for the Petrobras bribery scandal in Latin America, two of the biggest corruption cases of all time. The DOJ and SEC imposed penalties of 3.3 billion dollars against Goldman Sachs and 1.78 billion against Petroleo Brasileiro (Cassin, 2020, 2018). Since the FCPA's inception in 1977, many other large companies have been prosecuted and fined for at least 100 million dollars, including General Electric, KBR/Halliburton, Alstom, Ericsson, and Siemens. Between 1977 to 2019, over 580 corruption cases have been filed with nearly $17 billion in fines imposed.[1]

While the FCPA was originally designed to prosecute corrupt US-based companies that operate internationally, its scope greatly expanded in 1998. The 1998 amendment widened FCPA jurisdiction to include any domestic or foreign entity – firm or individual, that engages in any corrupt act which involves the US in any way. This includes, for instance, using US email servers and the US banking system to facilitate corrupt transactions, and holding meetings in any US territory during which corrupt deals are discussed. FCPA enforcement against US and non-US entities has been so far-reaching that Christensen et al. (2022) refer to FCPA enforcers as “policeman for the world".

Notwithstanding the rapid increase of FCPA enforcement and FCPA-related anti-corruption efforts around the world, little is known about their impact on economies. How does the FCPA affect the countries of the foreign public officials that receive bribes? Is FCPA en-

[1]See Campos et al. (2021) for the top ten cases as of January 2020 based on gross profits from bribes, bribes paid, and fines imposed.

forcement good for their economy?

Yes — for their *shadow* economy, that is. We demonstrate in this paper that after a FCPA case is filed against an entity that has paid bribes to foreign officials, the latter country's shadow economy as a percentage of GDP rises by as much as 0.27 percentage points, or approximately $540 million a year.

The hypothesis is that when corrupt public officials extract bribes from both legal and illegal markets, greater anti-corruption efforts in one market induces officials to switch their bribe-taking to the other. FCPA enforcement raises public officials' cost of bribe-taking from legal markets, relative to the cost of bribe-taking from illegal markets. This prompts officials to extract less bribes from legal entities and more from illegal ones, in exchange for 'allowing' more illegal production. In equilibrium, the size of illegal markets increases.

To test this bribe-switching hypothesis, we first estimate the effect of an FCPA case on the GDP per capita of the country whose officials are party to the case, as well as the effect on each of the expenditure components – consumption, investment, government expenditure, exports, and imports. We find that among countries with relatively low initial levels of corruption, GDP per capita and all components decrease. Among countries with higher initial levels of corruption, investment, exports, and imports go down, while GDP per capita is unchanged.

If FCPA enforcement increases the cost of, and therefore deters officials from, extracting bribes from, e.g., investment contracts, it would thus lessen the incentive of corrupt officials to approve such contracts. This, then, would decrease investment. That we find that investment falls after FCPA enforcement suggests that bribe-rents have also fallen; more so since we find a larger drop in countries with higher initial levels of corruption.[2]

However, even if some bribe-rents have decreased, it does not necessarily follow that total rents have fallen. In fact, we find no evidence that corruption scores improve after FCPA

[2]Christensen et al. (2022) finds similarly that foreign direct investment fell significantly in "high-corruption risk" countries following a surge in FCPA enforcement cases in 2004.

enforcement. Note also that while investment has decreased across all countries, only the low-corruption countries have experienced a drop in GDP per capita – GDP per capita in the high-corruption countries remain the same. This suggests that in the latter, corrupt public officials might be recovering lost bribe-rents from investment by extracting rents from other sources.

Where can corrupt public officials extract other rents to recoup lost ones? It is plausible that the wide scope of FCPA enforcement could deter corruption in many markets by making bribe-taking from many kinds of transactions more costly. Arguably, however, its deterrent effect on corruption in *illegal* markets would be smaller, if any. By their nature, illegal markets are hidden. Uncovering corruption in these markets is much more difficult since it requires piercing an already formidable veil of secrecy. In contrast, transactions in legal markets are relatively more transparent, making it less difficult to investigate whether such transactions violate the FCPA.

If FCPA enforcement has a greater corruption deterrent effect in legal, than in illegal, markets, then a public official who takes bribes from both markets would be induced to switch some of its bribe-taking to illegal markets. This would then cause illegal markets to grow. Note that the bribe-switching and growth in illegal markets should be more likely in countries in which public officials are already taking bribes from both legal and illegal markets. It would be easier to extract more bribes, than to start extracting bribes, from illegal markets when bribe-taking from legal markets becomes more costly.

Our primary proxy for the size of illegal markets is the size of the shadow economy as a percentage of GDP, constructed by Medina and Schneider (2019). To distinguish countries whose public officials are already likely taking bribes from both legal and illegal markets, we split our sample according to the initial levels of corruption, as well as the initial size of the shadow economy. Bribe-switching should be more apparent in countries where corruption is initially high and the shadow economy initially large.

As alternative indicators of illegal markets, we also look at homicide rates, tree loss – an indicator of illegal logging, and trade misinvoicing. A common way to misinvoice trade is to underreport imports in order to avoid paying import taxes. Trade misinvoicing thus depresses the (reported) value of imports. It is telling that imports of highly corrupt countries decrease after FCPA enforcement, while their investment and exports fall, thereby keeping their GDP per capita unchanged.

We find that after FCPA enforcement, shadow economies, homicide rates, and trade misinvoicing all go up, with the effects being more pronounced for countries that initially have higher corruption and larger shadow economies.

The paper makes several contributions to the corruption literature. First, we demonstrate that anti-corruption efforts, when focused only on certain kinds of transactions, can induce corrupt public officials to switch to other sources of rents (Olken and Pande, 2012). Olken (2007) finds that in Indonesia, the auditing of road projects decreased leakages, but increased nepotism, as officials ended up hiring up more relatives to work on the roads. Desierto (2021) shows that municipal mayors in the Philippines decrease bribe-taking when they can get more rents from appropriating government revenues. Burgess et al. (2012) provide evidence of rent–switching between oil and gas rents and illegal logging in Indonesia. Arbatskaya and Mialon (2020) provide a model of switching of investment contracts from US firms to foreign competitors when the FCPA is enforced against the former.

Second, we add to a small but growing literature on the economic analysis of the FCPA. Arbatskaya and Mialon (2020) formally analyze bribery and investment activities of firms that are subject to FCPA enforcement. With the recent exception of Christensen et al. (2022) which shows that FDI in high-corruption countries fall after FCPA enforcement, empirical papers have mostly focused on the effect of the FCPA on US firms and their competitiveness – Graham and Stroup (2016), Lippitt (2013), Wei (2000), and James R. Hines (1995). Our paper, in contrast, analyzes the effect of the FCPA on the foreign country whose public officials are recipients of the bribes. Causal identification is possible to the extent that foreign public officials have no control over the DOJ or SEC's decision to initiate a case against entities that have paid bribes to those officials. We exploit the fact that bribery is two-sided – the bribe offer by the entity has to be accepted by the foreign public official before bribes can actually be paid. Thus, FCPA enforcement against the entity exogenously triggers a decrease in bribe extraction by the foreign public official.

Lastly, the paper contributes to the nascent debate on whether corruption and the shadow economy are complements or substitutes. (See Nicolae et al. (2017) for a review.) Johnson et al. (1998), Choi and Thum (2005), and Dreher and Siemers (2009) posit that firms go underground in order to avoid government-induced distortions, e.g. bribe-taking. The implication is that as the latter becomes more ubiquitous, then the shadow economy increases as more firms go underground to avoid having to pay bribes. Illegal production thus substitutes for the corrupt transaction in legal markets. On the other hand, corruption and the shadow economy can be complements if illegal producers pay bribes to avoid getting caught (Hindriks et al. (1999), El-Shagi (2005), Dreher et al. (2009)). Combining both strands, Dreher and Schneider (2010) posit that in low-income countries, firms pay bribes to operate in the shadow economy – "underground activities require bribes and corruption", whereas in high-income countries, they pay to obtain large contracts in the legal sector. The authors thus suggest that corruption and the shadow economy are complements in low-income countries, but substitutes in high-income countries, and provide some limited evidence for this. Using cross-sectional data on 98 countries, they show that among the low-income countries, an increase in corruption perceptions is associated with an increase in the shadow economy, while there is no such association among the high-income countries.

In our paper, we allow for the possibility that bribery can take place both in legal and illegal markets. An increase in the expected costs of bribery in legal markets, e.g. due to FCPA enforcement, makes bribe-taking relatively easier in illegal markets, inducing corrupt officials to switch some of their bribe extraction to the latter. In exchange for paying more bribes, illegal producers are 'allowed' to increase production, and the shadow economy grows. We provide evidence using the most exhaustive panel of countries ever assembled to analyze the effect of the FCPA. Using a difference-in-differences (DID) framework, we employ the de Chaisemartin and D'Haultfœuille (2020a) estimator to accommodate heterogeneous treatment effects, as FCPA cases are filed at different time periods.[3] This also allows us to adopt a dynamic DID model and estimate pre-treatment placebo parameters, and to include a country-specific linear time trend. For robustness, we also generate results using the DID estimators of Callaway and SantâAnna (2020) and Cengiz et al. (2019).

The rest of the paper is organized as follows. Section 2 describes the data and identification strategy we use to test our bribe-switching hypothesis. Section 3 estimates the effect of the FCPA on GDP per capita, its expenditure components, and corruption scores, while Section 4 presents the main results — the effect of the FCPA on the shadow economy and other proxies for illegal markets. Section 5 concludes.

2 Methodology and Data

2.1 Conceptual Framework

The FCPA was signed into law in 1977, and was first enforced by the SEC and DOJ in 1978. The anti-bribery provisions of the law prohibit US persons, entities, and certain foreign issuers of securities from making illicit payments to any foreign official in exchange for obtaining or retaining business.[4] The law was then amended in 1998 to implement the requirements of the OECD Anti-Bribery Convention that signatories outlaw bribe payments

[3]The recent literature on DID models with heterogeneous treatment effects include de Chaisemartin and D'Haultfœuille (2020b), Callaway and SantâAnna (2020), Goodman-Bacon (2018), Sun and Abraham (2018), Athey and Imbens (2018), and Borusyak and Jaravel (2017).

[4]These are complemented by the accounting provisions of the law which requires issuers to accurately reflect the transactions of the corporation.

to foreign officials. Specifically, this amendment makes the anti-bribery provisions also apply to foreign persons and entities that act in furtherance of illicit payments within the territory of the United States. Such actions include

> "...placing a telephone call or sending an e-mail, text message, or fax form, to, or through the United States involves interstate commerce–as does sending a wire transfer from or to a U.S. bank or otherwise using the U.S. banking system, or traveling across state borders or internationally to or from the United States (pg. 10, FCPA Resource Guide (2015))."

We focus on the effect of this 1998 amendment. Compared to the original law, the amended version, with its wider scope, has greater potential to deter corruption in *foreign* countries, which comprise our population of interest. Deterrence can occur through direct or indirect ways. The FCPA can be directly enforced against foreign officials if they engage in corrupt activity through US channels. An example is Heon-Cheol Chi who was Director of the Earthquake Research Center at the Korea Institute of Geoscience and Mineral Resources. The DOJ was able to indict him for laundering bribe-money through the Bank of America.

Indirectly, FCPA enforcement can trigger anti-corruption efforts in foreign countries whenever the US shares information with local authorities. In fact, the US and other signatory countries to the 1997 OECD Anti-Bribery Convention are obliged to provide mutual legal assistance and evidence sharing (Brewster, 2017). Note, then, how large corruption scandals usually involve investigations and prosecutions in multiple jurisdictions – e.g., scandals involving Siemens, Technip, Halliburton, BAE systems (Brewster, 2017) and, of course, 1MDB and Petrobras.[5] The Convention also aims that, with the example of the FCPA, other countries will also institutionalize their own anti-corruption efforts by, e.g., outlawing bribery.

[5]As of 2018, there were 44 signatories to the Convention, 37 of which are members of the OECD.

Thus, by exposing corrupt transactions involving foreign public officials, FCPA enforcement can prompt the host countries to conduct their own investigations or, in some cases, allow the US to directly prosecute the foreign officials. FCPA enforcement can then increase the costs of, and decrease the incidence of, bribe-taking by foreign public officials. In turn, lower corruption in their countries can lead to higher growth (Mauro, 1995; Mo, 2001; Gründler and Potrafke, 2019), investment (Cieślik and Goczek, 2018; Zakharov, 2019), and entrepreneurship (Bologna and Ross, 2015; Dutta and Sobel, 2016; Colonnelli and Prem, 2020).

We first estimate the effect of FCPA enforcement on the GDP per capita of the foreign countries whose public officials were implicated in a FCPA case. To verify that the mechanism is through a decrease in bribe-taking, we test whether FCPA enforcement has an impact on the countries' corruption perception scores. We then probe deeper by looking at the effect on each expenditure component of GDP – consumption, investment, government expenditures, exports, and imports.

We find that GDP per capita is unchanged for countries that have high initial levels of corruption.[6] That is, the FCPA seems to have no effect on countries which could have had large marginal gains from anti-corruption efforts. Perhaps anti-corruption authorities in countries with high initial levels of corruption do not act on information revealed by FCPA enforcement. Indeed, we find no evidence that bribe-rents decrease after FCPA enforcement – corruption perception scores among highly corrupt countries are unchanged. However, for countries that have low initial levels of corruption – i.e., those that could be more responsive to FCPA enforcement – their GDP per capita *falls* after enforcement. Moreover, their corruption perception scores appear to worsen.

The results become more puzzling when looking at the components of GDP. Although their GDP per capita remains the same, highly corrupt countries appear to experience re-

[6]For initial corruption scores, we use the World Bank's Control of Corruption Index for the year 1996, the first year for which the index is available.

ductions in investment, exports, and imports after FCPA enforcement. Such trends, on their own, are not surprising since a loss of bribe-rents due to anti-corruption efforts can discourage corrupt public officials from facilitating business ventures and investment. Indeed, Beck et al. (1991), James R. Hines (1995), and Graham (2016) provide some evidence that the FCPA decreases US firms' competitiveness. Arbatskaya and Mialon (2020) propose a model showing how total investment in the foreign country can decrease after the FCPA is enforced against US firms, when the competitors of these firms cannot bribe. What is striking, however, is that despite the fall in its various components, GDP per capita appears unchanged.

If the usual sources of bribe-rents such as investment contracts slow down, but total bribe-rents are preserved (as suggested by non-improving corruption scores), from where are the lost rents being recouped?

We investigate the possibility that FCPA enforcement induces bribe-switching from legal to illegal markets. If corrupt public officials can take bribes both from legal enterprises by, e.g., awarding contracts, and from illegal producers who want to avoid detection and prosecution, then an increase in the cost of taking bribes from legal markets can induce officials to decrease their bribe-taking from legal markets and increase it from illegal markets. To extract larger bribes from the latter, public officials enforce less against illegal producers – a la Becker et al. (2006) and Desierto and Nye (2017), thereby increasing the size of illegal markets. This could explain why aggregate economic activity and corruption scores do not change – bribe-rents are preserved by extracting more bribes from illegal producers whose increased activities make up for the decrease in legal transactions.[7].

As an empirical test, we estimate the effect of FCPA enforcement on the size of the illegal markets of the countries whose public officials were implicated in a FCPA case. We use the size of the shadow economy (as percentage of GDP) as a proxy, as constructed by Medina

[7]For a more formal rendition of our bribe-switching hypothesis, we refer the reader to Appendix A

and Schneider (2019). This is a measure of “illegal activities (and) unreported income from the production of legal goods and services, either from monetary or barter transactions".[8] We not only show that the shadow economy significantly rises after FCPA enforcement, but that the growth is larger for countries that are initially more corrupt, and for countries with initially large shadow economies, in which it is more likely for corrupt public officials to take bribes from both legal and illegal markets.[9] As the shadow economy includes unreported incomes from *legal* production, we also estimate the effect on other, more direct, indicators of illegal activities, viz., trade misinvoicing – an example of which is the underreporting of imports to avoid customs duties, homicide rates (per 100,000 people), and tree loss coverage (potentially due to illegal logging and mining). While data on these measures are more limited, they nevertheless provide some evidence of a rise in illegal activity following FCPA enforcement for countries that are initially more corrupt and have larger shadow economies.

Table 1 lists the main outcome variables we use; Table 2 lists the associated summary statistics. The next section describes the treatment variable.

[8] See https://www.imf.org/external/pubs/ft/issues/issues30/.

[9] To measure the initial size of the shadow economy, we use the average size in the period 1990-1997.

Table 1: Variable Names, Brief Descriptions, & Sources for Dependent Variables

Name	Brief Description	1st Available Year[1]
Economic Output		
Real GDP per-capita	Expenditure Side Real GDP per-capita (PWT)[2]	1978
Economic Components		
Consumption	Real consumption per-capita (PWT)	1978
Investment	Real investment per-capita (PWT)	1978
Government	Real government per-capita (PWT)	1978
Exports	Real exports per-capita (PWT)	1978
Imports	Real imports per-capita (PWT)	1978
Corruption Reform		
World Bank Corruption	Corruption index with a scale of -2.5 (most corrupt) to 2.5 (least corrupt) (WBG)	1996
ICRG Corruption	Corruption index with a scale of 1 (most corrupt) to 6 (least corrupt) (ICRG)	1984
Illegal Activity		
Shadow Economy	Shadow economy as a % of official GDP (MS)	1991
Other Illicit Activities		
Homicide Rate	Homicides per 100,000 people (UNODC)	1990
Tree Loss	Tree loss as a % of total hectares (GFW - WRI)	2000
Trade Misinvoicing	Value gap in trade as a % of total trade (GFI)	2008

[1] First available year relative to the 1978 start date of the FCPA program.
[2] *Sources*: (1) PWT - Penn World Tables Version 9.1. (2) MS - Medina and Schneider (2019). (3) WBG - World Bank Governance Indicators. (4) ICRG - International Country Risk Guide. (5) UNODC - United Nations Office on Drugs and Crime. (6) Global Forest Watch - World Resources Institute. (7) Global Financial Integrity.

Table 2: Summary Statistics for Dependent Variables

Name	Obs.	Mean	Std Dev	Min	Max
Economic Output					
Real GDP per-capita	4,982	14,998	17,270	223	153,458
Economic Components					
Consumption	4,926	7,983	8,925	166	224,619
Investment	4,926	4,050	6,370	8.766	183,765
Government	4,926	2,759	3,569	12.738	96,165
Exports	4,926	6,774	13,859	0.054	140,354
Imports	4,926	7,703	17,032	0.267	522,304
Corruption Reform					
World Bank Corruption	4,406	-0.025	0.999	-1.869	2.470
ICRG Corruption	3,637	2.871	1.290	0	6
Illegal Activity					
Shadow Economy	4,212	31.122	12.751	5.1	70.5
Other Illicit Activity					
Homicide Rates	3,965	8.027	12.226	0.000	141.723
Tree Loss	2,907	0.181	0.289	0.000	3.287
Trade Misinvoicing	1,175	19.763	5.887	0.030	87.240

Notes: All per-capita variables (GDP and GDP components) and homicide rates enter regressions in logged form. All other dependent variables enter regressions in their raw form.

2.2 Treatment Variable and Sample

We use data on FCPA enforcement cases compiled by the FCPA Clearinghouse at Stanford Law School. To focus on the effect of the 1998 reform, and to maximize the number of observations for which data are available, we include in our sample all cases from 1990 through 2019.[10] For each case, information is provided on the identity of the US person or entity against which the case is filed, the date in which the case was initiated, the prosecuting agency (SEC or DOJ), the amount of the bribe paid, the country in which it was paid, and the amount of the sanction or settlement. Since we can calculate, for each country in each

[10]While some variables are available for a much longer time period (e.g., GDP), most others become available only after 1990. Focusing on the post-1990 period also allows us to focus on the post-Soviet era.

year of the sample, the number of FCPA cases involving that country, we are able to form a country-year panel of FCPA cases.

Prior to 1998, there were only a total of 42 FCPA cases filed over a 20-year period. In addition, the size of the penalties (fines) in these early cases were comparatively small. As noted in Brewster (2017), even the tenth highest fine in more recent years (post-reform) is more than twice the *combined* penalties from the first two decades of the program. After the 1998 reform, the number of cases jumped – 544 cases filed between 1998 to 2019. These include cases involving non-US firms that are covered by the 1998 amendment. In 2019, for instance, 8 out of the 14 enforcement cases filed against corporations were against foreign entities. The total amount of settlements from the 2010 cases alone was almost $3 billion US dollars, and about half of which are from the cases against foreign entities.[11]

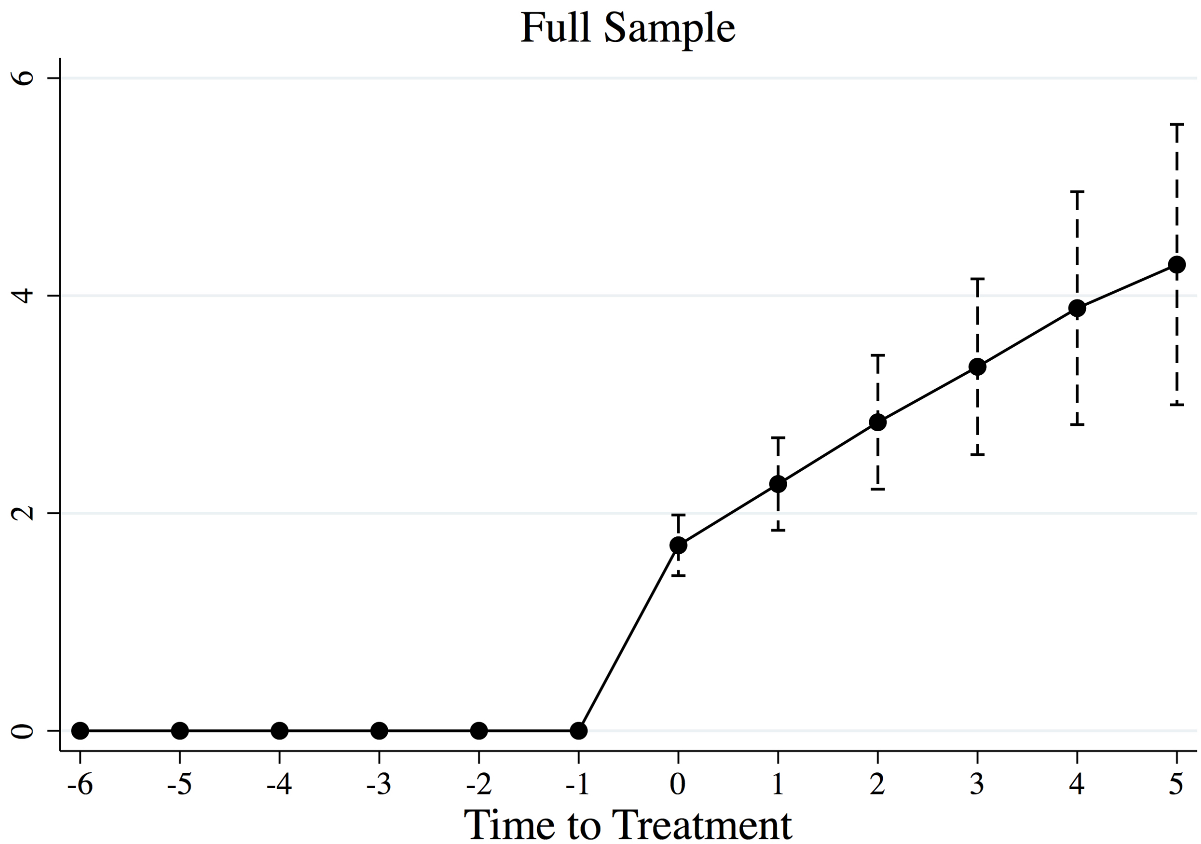
We assign zero number of cases to the country from 1990 until the first year after 1998 (i.e. post amendment) that the country experiences its first FCPA enforcement case.[12] Within the first year post amendment, there is already some variation in the number of cases across countries. This is to be expected since the DOJ and SEC can actually simultaneously file separate cases. Moreover, many countries also experience subsequent enforcement after the first case is filed. Figure 1 summarizes this pattern. Time 0 represents the country's first year of experiencing FCPA enforcement, which generates an average of 1.7 cases across all the countries in the sample. The number of cases grows thereafter.

Figure 2 splits the sample evenly according to the countries' initial (pre-1998) corruption perception scores, and shows that more cases are filed involving public officials in relatively more corrupt countries. This pattern can help allay concerns regarding potential biases of the SEC and DOJ. That is, if cases are filed based on merit, one would expect the SEC and DOJ to file more cases involving public officials in relatively more corrupt countries.

[11]See https://fcpaprofessor.com/fcpa-enforcement-actions-foreign-companies-oecd-convention-peer-countries-4/.

[12]The actual number of cases in the pre-treatment (1990-1997) period is low – only 15 cases across 9 countries. In Appendix C, we drop these 9 countries and obtain similar results (see Tables **??** through **??**).

Figure 1: Treatment - Cumulative Sum of FCPA Cases - Full Sample



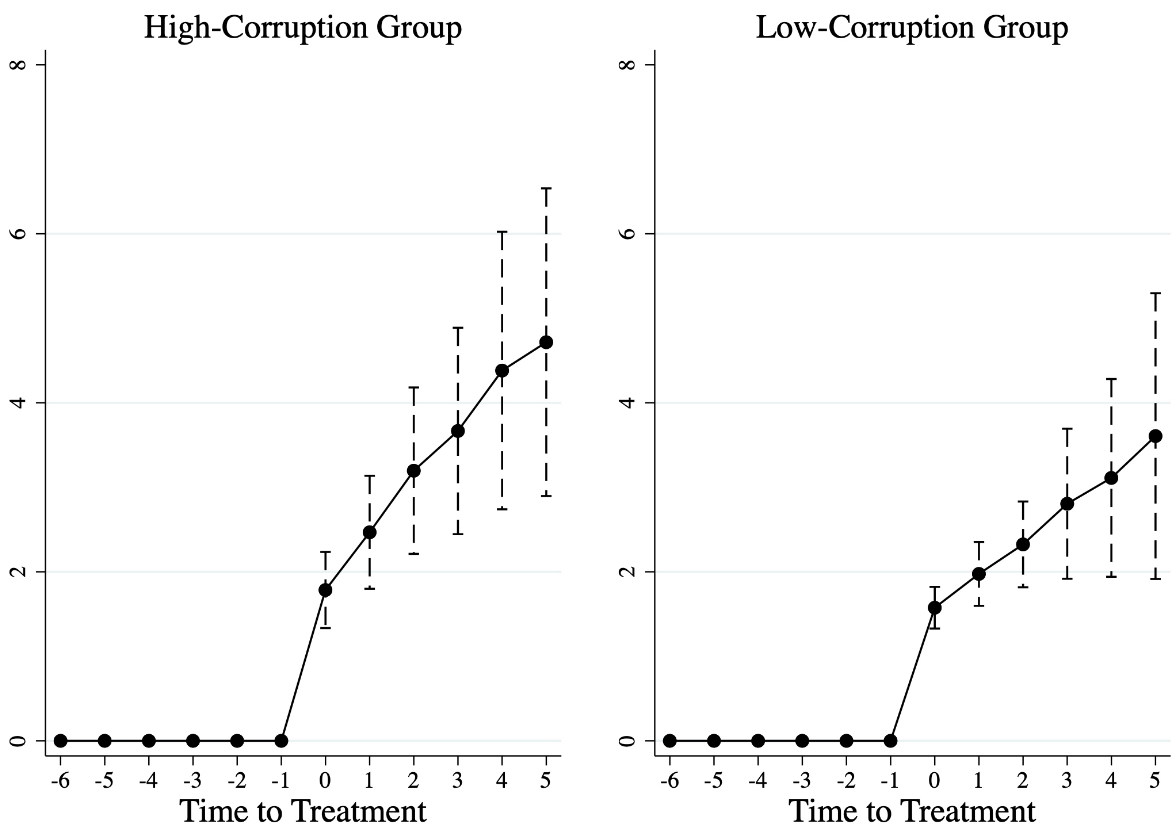
Notes: Bars correspond to 95% confidence intervals.

To account for this difference, we also run regressions separately for countries that have relatively higher, and those that have relatively lower, initial corruption perception scores.[13]

The pattern of cases filed post 1998 suggests that being treated with FCPA enforcement is like experiencing changes in treatment "dosage" over time. As de Chaisemartin and D'Haultfœuille (2020a) discuss, this type of treatment can be extremely complicated to interpret. We thus follow their approach of first defining the initial instance of enforcement as a binary treatment. Specifically, our treatment variable equals one in the year in which the first FCPA case was filed, and remains one thereafter. After estimating the effect of this

[13]As a further robustness check of biases in enforcement due to, e.g. political targeting of certain countries, we also distinguish cases filed by the SEC from those filed by the DOJ, as the SEC is an independent agency and may thus be more insulated from political pressures. As Appendix C Tables **??** through **??** report, there is no difference in results between SEC and DOJ cases.

Figure 2: Treatment - Cumulative Sum of FCPA Cases - High-Corruption versus Low-Corruption Group



Notes: Bars correspond to 95% confidence intervals. The corrupt group corresponds to those countries with an initial corruption perception score at the 50$^{\text{th}}$ percentile or lower prior to 1998. Likewise, the non-corrupt group corresponds to those countries with a corruption perception score above the 50$^{\text{th}}$ percentile prior to 1998.

binary treatment variable, we then divide it by the yearly case count to get an estimate of the effect of a single FCPA case.[14]

2.3 Empirical Strategy

To test whether the (binary) treatment variable previously described has an effect on our outcome variables, denote the treatment as $FCPA_{it}^{d}$, which becomes one in the first year of FCPA enforcement involving country i and remains one thereafter, d periods from t. We

[14]That we first estimate the effect of a binary treatment makes our approach comparable to the plethora of newly proposed DID estimators, which we also use as robustness check.

then let $d = \{l, l+1, l+2, ...0, 1, 2, ..., L\}$, with $l < 0$ and $L > 0$. Thus, $d = -1$ ($d = l$) is the first year ($|l|$ years) prior to country i's first FCPA enforcement case; $d = 0$ is the year of first enforcement, and $d = L$ is L years after this.[15]

We adopt a dynamic specification to allow for the possibility that the treatment generates different effects over time:

$$Y_{it} = \sum_{d=l}^{L} \alpha_d FCPA_{it}^d + \mu_t + \eta_i + \beta_i \gamma_{it} + u_{it}, \tag{1}$$

where μ_t are year fixed effects, η_i country fixed effects, γ_{it} is a country-specific time trend, and u_{it} the error term. Standard errors are clustered by country and calculated using 250 bootstrap replications.

One could estimate (1) using OLS, but this can yield biased estimates if there are heterogeneous treatment effects. de Chaisemartin and D'Haultfœuille (2020b,a) have shown that OLS regression of two-way fixed effects models (TWFE) with binary or non-binary treatments estimates the weighted average of the treatment effects across groups, where the weights can be negative. This can then yield estimates that are opposite of their true sign.

More generally, treatment heterogeneity raises the primary issue of whether the control units are appropriate. In typical TWFE models, previously-treated units act as controls for newly-treated units, but this may not be suitable when treatment effects change through time. Indeed, many new estimators have been proposed precisely to address this problem.[16] The de Chaisemartin and D'Haultfœuille (2020a) estimator, for instance, uses both never-treated and not-*yet* treated units as controls. (Already-treated units are never used as controls). Meanwhile, the Callaway and SantâAnna (2020) estimator uses only never-treated units as controls. These two estimators yield similar results and only differ in the choice of control units. Another estimator that uses only never-treated units as controls is the stacked

[15]Recall from 2.2 that by construction, $FCPA_{it}^d = 0$ for $d < 0$.

[16]De Chaisemartin and D'Haultfoeuille (2022) provide a helpful summary of these new estimators and research in this area.

difference-in-difference approach à la Cengiz et al. (2019). Separate datasets are created for each treatment group, which are then stacked together to estimate an average treatment effect.

Our main results are generated using the de Chaisemartin and D'Haultfœuille (2020a) estimator, as it can accommodate linear time trends which are apparent in our data.[17] For robustness, we also run regressions without a linear time trend. We also generate results using the Callaway and SantâAnna (2020) and Cengiz et al. (2019) estimators. For the latter, we define a treatment group according to the year of the first instance of FCPA enforcement in a treated country, and estimate an average treatment effect across these groups. Finally, we also estimate (1) by OLS to generate TWFE coefficients for comparison.[18]

We implement the de Chaisemartin and D'Haultfœuille (2020a) estimator in $STATA$ using the *did_multiplegt* module. This yields output analogous to an event study design where the placebo option estimates parameters $\{\alpha_d\}$, $d < 0$, while the dynamic option estimates dynamic treatment effects $\{\alpha_d\}$, $d \geq 0$. In both cases, the coefficients are to be interpreted as long-run differences between the period in question (e.g., $d = L$) and the placebo period immediately prior to the treatment ($d = -1$). Thus, for all cases, the period $d = -1$ will have a coefficient equal to zero by definition (i.e., this is the reference year). Each estimated treatment effect can then be assessed relative to this placebo period, provided that it is normalized by the number of cases. That is, by dividing parameter estimates by the average number of cases between year d and $d = -1$, one can obtain the effect of an additional FCPA case. Note that doing so does not separately identify the effect of the first case/s and the effects of the subsequent cases after the initial year. Normalizing only allows us to gauge whether the effect of *any* case increases or decreases through time. Because the

[17] This is a modified version of the de Chaisemartin and D'Haultfœuille (2020b) estimator that is designed to capture both contemporaneous and dynamic treatment effects in the presence of treatment heterogeneity.

[18] The main results using the de Chaisemartin and D'Haultfœuille (2020a) estimator are reported in the main text, while results using the alternative estimators are summarized in Appendix B. These results are generally similar to the main ones, but we discuss some important differences in the main text.

choice of the number of pre- and post- treatment periods is arbitrary, we report results using both a two-year (in Tables) and five-year window (in Graphs).

We also estimate the parameters separately for countries with high (H) and low (L) initial corruption perception scores, to serve as falsification test of our bribe-switching hypothesis. If countries in group H have more widespread and endemic corruption, whereas those in group L experience more isolated instances of corruption, it is then in group H that corrupt officials are more likely to take bribes both from legal and illegal markets and, thus, more able to switch to more bribe-taking from the latter after FCPA enforcement. Superscripting (1) by group, we then estimate:

$$Y_{it}^{H} = \sum_{d=l}^{L} \alpha_d^H FCPA_{it}^{dH} + \mu_t^H + \eta_i^H + \beta_i^H \gamma_{it}^H + u_{it}^H \tag{2}$$

$$Y_{it}^{L} = \sum_{d=l}^{L} \alpha_d^L FCPA_{it}^{dL} + \mu_t^L + \eta_i^L + \beta_i^L \gamma_{it}^L + u_{it}^L \tag{3}$$

We expect $\hat{\alpha}_d^H = \hat{\alpha}_d^L$ in the pre-treatment periods, that is, when $d < 0$, but that $\hat{\alpha}_d^H \neq \hat{\alpha}_d^L$ in the post treatment periods. Whether α_d^H is greater than or less than $\hat{\alpha}_d^L$ post treatment depends on the outcome of interest and implicit mechanism. Suppose Y is a measure of economic activity. If an FCPA case deters corrupt public officials from extracting bribes from legal markets, but they do *not* switch to taking bribes from illegal markets, then it might be that $\hat{\alpha}_d^L \geq \hat{\alpha}_d^H$ in most, if not all, post treatment periods $d \geq 0$. This is what would be expected if countries with lower corruption to begin with are more successful in conducting their own investigations and in pursuing other anti-corruption efforts that are spurred by FCPA enforcement.

To support this idea, one could then run regressions with Y as a measure of corruption. If better economic outcomes are due to successful anti-corruption efforts, then it must also be the case that $|\hat{\alpha}_d^L| \geq |\hat{\alpha}_d^H|$ when $d \geq 0$ – FCPA enforcement subsequently lowers corruption in low corruption countries by at least as much as it does in high corruption countries.

On the other hand, if bribe-switching did occur between legal and illegal markets, it would be more likely in countries with widespread corruption, in which public officials are likely to obtain rents from multiple sources, including illegal producers who want to avoid detection and prosecution. In this case, one could also expect the effect on economic activity Y to be such that $\hat{\alpha}_d^L \geq \hat{\alpha}_d^H$ for most post treatment periods. This is because public officials in low corruption countries might be more willing to substitute towards non-corrupt contracts/enterprises, whereas those in high corruption countries might be more able to preserve rents by switching their bribe extraction from legal, to illegal, sources. Necessary for this, however, is evidence that high corruption countries do not become less corrupt, as contrary evidence would suggest that their bribe-rents are *not* preserved. One could then estimate (2) and (3) with Y as indicators of illegal activities, and show that $\hat{\alpha}_d^L < \hat{\alpha}_d^H$ when $d \geq 0$, with $\hat{\alpha}_d^L$ possibly equal to zero if there were no bribe-switching in low corruption countries.

We conduct another, more direct, falsification test of our bribe-switching hypothesis by estimating (2) and (3) for countries that have, respectively, high and low initial size of illegal markets, as proxied by the initial (pre-1998) size of the shadow economy. Bribe-switching between legal and illegal markets should be more likely for countries that already have large illegal markets to begin with, irrespective of whether these countries have high or low initial corruption scores.

3 Economic Activity after FCPA Enforcement

We begin by estimating the effect of FCPA enforcement on (logged) GDP per capita. We first report results using a two-year pre-post treatment window for both the overall sample (Table 3) and the high- and low-corruption groups (Table 4). Each table reports the treatment effect estimate throughout the placebo period ($d = -3$ and $d = -2$) and the treatment period ($d = 0$, $d = 1$, and $d = 2$). Recall that, analogous to a standard event study design, the pre-treatment and post-treatment coefficients are interpreted relative to the reference period ($d = -1$). For the high- versus low-corruption groups, we also calculate a T-Statistic to test if $\hat{\alpha}_d^H - \hat{\alpha}_d^L$ is different from zero.[19] We report the T-Statistic as positive if $\hat{\alpha}_d^H > \hat{\alpha}_d^L$, negative if $\hat{\alpha}_d^H < \hat{\alpha}_d^L$, and gauge significance using the relevant one-sided thresholds.[20] We then expand the pre-post treatment window to five years and summarize the results in Figures 3 and 4.

As shown in Table 3 and Figure 3, FCPA enforcement does not have a significant effect on GDP per capita for the full sample. There is also no impact on GDP per capita for the high-corruption group. However, GDP per capita falls for the low-corruption group. While these effects are not statistically different from one another, they do suggest that the effect of FCPA enforcement is not homogeneous across country groups making the aggregate results less useful. As such, and given our hypothesis regarding bribe-switching, our remaining results focus only on the high- versus low-corruption groups. Graphs summarizing the results using the full sample of data for each of the remaining outcome variables is available in our Online Only Appendix 1.

To gauge the impact of a single FCPA case, we normalize the treatment effects by dividing the coefficients reported in Table 4 by the average number of cases in a given year. For example, in Year 0 (the initial year of the treatment), low-corruption countries experience 1.58 cases on average. Thus, dividing the coefficient for Year 0 (-0.030) by 1.58 shows that a single case reduces logged GDP per capita by 0.019, or GDP per capita by approximately 1.90 percent. We can then repeat this process for each year, normalizing by the appropriate average case counts. After doing so, we find that GDP per capita falls by approximately

[19] Because our estimates are made using two independent samples with a covariance of zero, we can estimate our T-Statistic using the following formula:

$$T - Statistic = \frac{\hat{\alpha}_d^H - \hat{\alpha}_d^L}{\sqrt{(SE_d^H)^2 + (SE_d^L)^2}}$$

[20] Two-sided thresholds could be used as well, but since we are interested in whether the effects differ in specific directions we use the one-sided thresholds here. The calculation of the T-Statistics is the same in both cases.

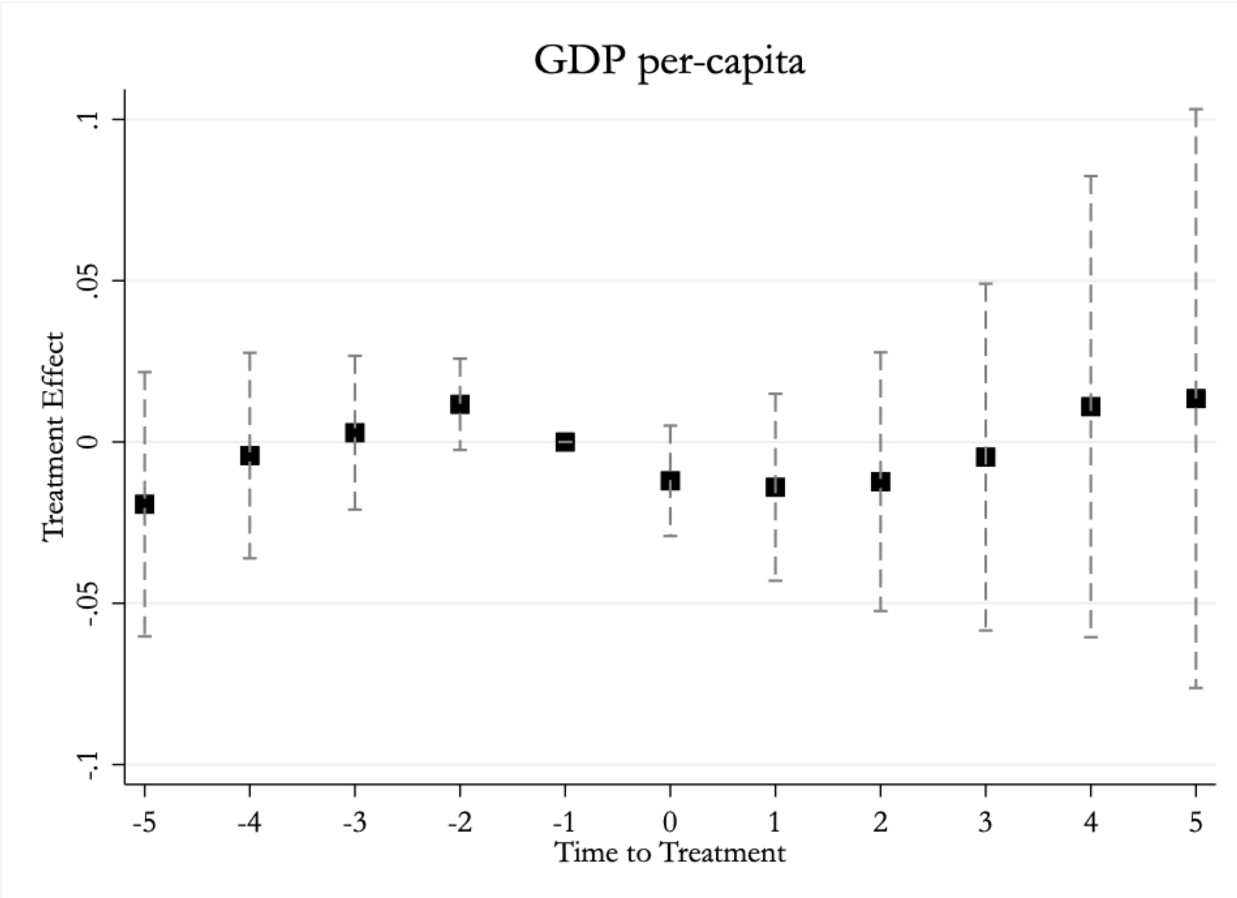
1.90 percent in Year 0, 2.7 percent in Year 1, and 2.8 percent in Year 2. These effects are all statistically significant. Given that the annual growth rate for per capita GDP across countries hovers around 2 percent on average, these are meaningful effects. Normalized coefficients for all of our main estimates are summarized in Table A1.

Table 3: Dynamic Effect of Corruption Enforcement on GDP per-capita-C&D (2020a) Estimator for the Full Sample

	Lower Bound (LB)	Coefficient	Upper Bound (UB)	Obs.
Year -3	-0.021	0.003	0.027	2,604
Year -2	-0.002	0.012	0.026	2,713
Year 0	-0.029	-0.012	0.005	2,639
Year 1	-0.043	-0.014	0.015	2,460
Year 2	-0.052	-0.012	0.028	2,282

Notes: Lower bound (LB) and upper bound (UB) estimates made with 95% confidence intervals. Bold numbers indicate statistical significance at this level. All estimations include a country-specific time trend.

Figure 3: Dynamic Effect of FCPA Enforcement on GDP per-capita for the Full Sample



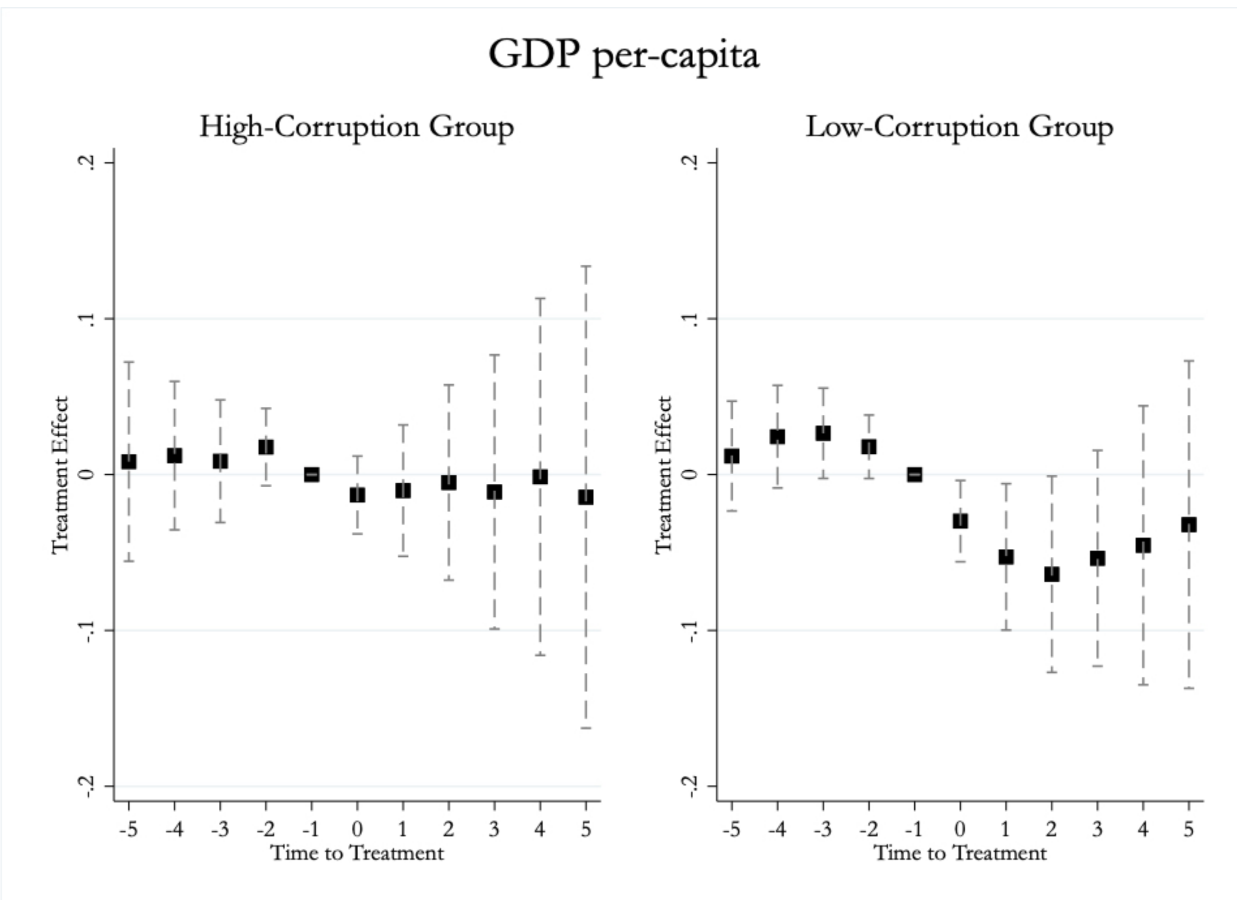
Notes: Bars correspond to 95% confidence intervals.

Table 4: Dynamic Effect of Corruption Enforcement on GDP per-capita- C&D (2020a) Estimator for High–Corruption versus Low–Corruption Groups

Year	High–Corruption 0 - 50			Low–Corruption 50 - 100			Difference?
	LB	Coefficient	UB	LL	Coefficient	UB	T-Stat
Year -3	-0.031	0.009	0.048	-0.002	0.027	0.055	-0.720
Year -2	-0.007	0.018	0.042	-0.003	0.018	0.038	-0.012
Year 0	-0.038	-0.013	0.012	**-0.056**	**-0.030**	**-0.004**	0.910
Year 1	-0.052	-0.010	0.032	**-0.100**	**-0.053**	**-0.006**	1.322
Year 2	-0.068	-0.005	0.057	**-0.127**	**-0.064**	**-0.001**	1.300

Notes: Lower bound and upper bound estimates made with 95% confidence intervals. Bold numbers indicate statistical significance at this level. T-statistics assume infinite degrees of freedom and are calculated using a one-tailed test ($\hat{\alpha}_d^H - \hat{\alpha}_d^L$). There are an average of 960 and 1,008 observations per estimated treatment effect for the high– and low–corruption groups, respectively. All estimations include a country-specific time trend.

Figure 4: Dynamic Effect of FCPA Enforcement on GDP per-capita for the High-Corruption Group (50th percentile or below) and Low-Corruption Group (greater than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

The results suggest that the 1998 FCPA reform is not fulfilling the broader mandate of the OECD Anti-Bribery Convention of lowering corruption worldwide. In fact, as a more direct indication of this, corruption scores for either the high- or low-corruption groups have not improved. We explore the effect of FCPA enforcement on corruption perceptions using the World Bank Control of Corruption measure and the Political Risk Services Corruption Index. For both measures, a higher value implies *less* corruption. These results are reported in Table 5, with the five-year window results summarized in Figure 5. There is no evidence that corruption scores improved for either group – on the contrary, corruption perceptions may have worsened in the low-corruption group.[21]

Thus far, the results suggest that the 1998 FCPA reform does not improve corruption nor total economic activity of the relatively more corrupt countries, but has deleterious effects on the relatively less corrupt, i.e., increases corruption perceptions and lowers their GDP per capita. To probe deeper into such patterns, we estimate the effect of FCPA enforcement on the expenditure components of GDP per capita. Since expenditure-based GDP is, by identity, the sum of these components, the overall effect of FCPA enforcement on GDP should be consistent with the effect on each component.[22] Thus, for instance, if GDP is unchanged, then a fall in any of its components should be accompanied by an increase in any of its remaining components, or a decrease in the case of imports.[23]

[21] Of course, this could be driven by inherent biases in measures of corruption perception. Corruption perception indices are heavily influenced by external factors (e.g., FCPA enforcement media coverage) and can change even when corruption *experience* remains the same (Olken, 2009; Donchev and Ujhelyi, 2014). In addition, as shown in Appendix B, these particular results are not robust across estimators. The point, however, is that we see no clear evidence that corruption has decreased for initially highly corrupt countries.

[22] We exclude Azerbaijan and the Bahamas from these specific results as their reported component shares of GDP are all negative, excluding imports.

[23] While this identity holds for much of our sample, some countries have a non-negligible residual component share. This is often refereed to as statistical discrepancy (i.e., the difference between expenditure-based and income-based GDP estimates). More specifically, approximately 10% of the total sample have a discrepancy above 15% in absolute value. Because statistical discrepancy can be indicative of increasing informality (Medina and Schneider, 2018), we additionally explore whether the residual component changes in absolute value following enforcement. We find no evidence that FCPA enforcement affects this residual component in any group (full sample, high-, or low-corruption). We additionally explore if excluding countries with high levels of discrepancy (above 15%) and confirm our main findings are unchanged. These results are available upon request.

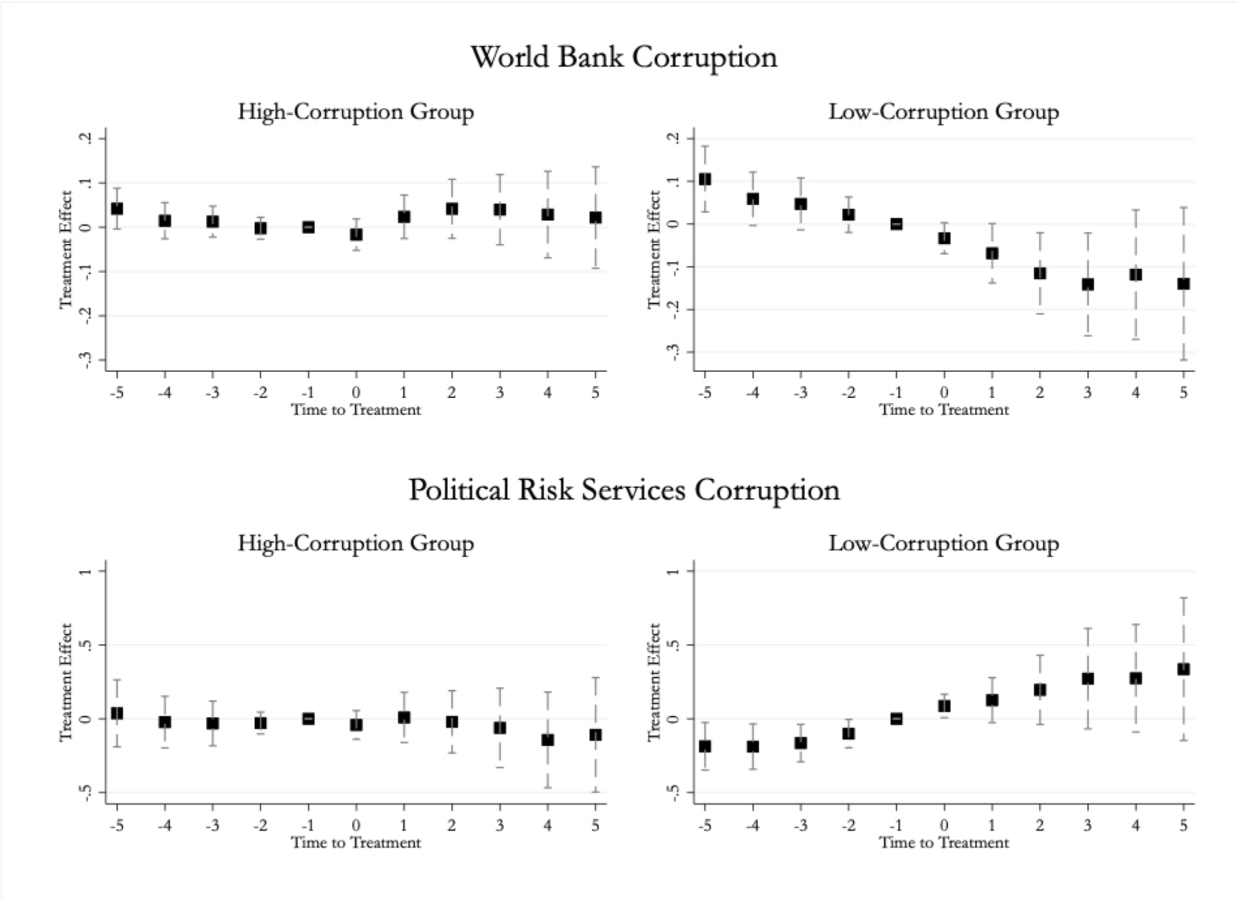
Table 5: Dynamic Effect of Corruption Enforcement on Corruption Perceptions - C&D (2020a) Estimator for the High–Corruption versus Low–Corruption Groups

Year	High–Corruption 0 - 50			Low–Corruption 50 - 100			Difference?
	World Bank Corruption						
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.022	0.013	0.048	-0.014	0.047	0.108	-0.964
Year -2	-0.027	-0.002	0.022	-0.020	0.022	0.063	-0.985
Year 0	-0.052	-0.017	0.019	-0.069	-0.033	0.003	0.633
Year 1	-0.026	0.023	0.073	-0.138	-0.068	0.001	**2.115**
Year 2	-0.025	0.042	0.108	**-0.210**	**-0.115**	**-0.020**	**2.653**
	Political Risk Services Corruption						
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.183	-0.032	0.12	-0.292	-0.165	-0.038	1.320
Year -2	-0.103	-0.029	0.045	-0.196	-0.101	-0.005	1.161
Year 0	-0.139	-0.042	0.055	**0.008**	**0.087**	**0.166**	**-2.014**
Year 1	-0.161	0.009	0.179	-0.027	0.126	0.279	-1.002
Year 2	-0.231	-0.021	0.19	-0.039	0.196	0.431	-1.347

item *Notes*: Lower bound (LB) and upper bound (UB) estimates made with 95% confidence intervals. Bold rows and t-statistics are statistically significant at this 5% level. For the World Bank Corruption measure, there are an average of 1,065 and 1,139 observations per estimated treatment effect for the high–corruption group and low–corruption group, respectively. Likewise, for PRS, there are an average of 720 and 750 observations per estimated treatment effect for the high–corruption group and low–corruption group, respectively. All estimations include a country-specific time trend.

The results for the two-year window are presented in Table 6. Results for the five-year window are available in Appendix B Figures B4 through B8. FCPA enforcement appears to decrease investment, exports, and imports for both groups. However, the point estimates are larger (in magnitude) for the high-corruption group. The decrease in their investment and exports is accompanied by a large decrease in their imports – recall that the GDP per capita of these countries are unchanged by FCPA enforcement (Table 4). In addition, while insignificant, the effect on government spending is positive in these countries. In contrast, that GDP per capita falls for the low-corruption group is consistent with the point estimates being negative for every component of their GDP.

Figure 5: Dynamic Effect of FCPA Enforcement on Corruption Perceptions for the High-Corruption Group (50th percentile or below) and Low-Corruption Group (greater than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

Table 6: Dynamic Effect of Corruption Enforcement on GDP components - C&D (2020a) Estimator for the High–Corruption versus Low–Corruption Groups

Year		High–Corruption 0 - 50			Low–Corruption 50 - 100		Difference?
				Consumption			
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.029	0.009	0.048	-0.040	0.001	0.042	0.286
Year -2	-0.037	0.007	0.051	-0.052	-0.015	0.023	0.733
Year 0	-0.064	-0.029	0.005	-0.065	-0.022	0.021	-0.242
Year 1	-0.072	-0.031	0.010	-0.050	-0.018	0.014	-0.476
Year 2	-0.127	-0.061	0.004	-0.075	-0.030	0.014	-0.768
				Investment			
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.048	0.053	0.153	-0.092	0.000	0.091	0.770
Year -2	-0.016	0.040	0.097	-0.065	0.009	0.083	0.661
Year 0	**-0.140**	**-0.090**	**-0.039**	**-0.113**	**-0.057**	**-0.002**	-0.841
Year 1	**-0.222**	**-0.137**	**-0.053**	-0.128	-0.061	0.007	-1.390
Year 2	-0.216	-0.106	0.005	-0.126	-0.043	0.041	-0.891
				Government Spending			
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.056	0.012	0.081	-0.088	-0.026	0.037	0.800
Year -2	-0.012	0.025	0.061	-0.062	0.003	0.067	0.576
Year 0	-0.063	0.009	0.081	-0.086	-0.039	0.008	1.105
Year 1	-0.087	0.005	0.096	-0.113	-0.052	0.009	1.013
Year 2	-0.110	0.022	0.155	-0.158	-0.070	0.018	1.132
				Exports			
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	**0.004**	**0.078**	**0.152**	-0.203	-0.037	0.129	1.232
Year -2	-0.024	0.062	0.149	-0.226	-0.061	0.103	1.305
Year 0	**-0.161**	**-0.091**	**-0.021**	**-0.110**	**-0.056**	**-0.003**	-0.772
Year 1	-0.200	-0.093	0.015	**-0.173**	**-0.088**	**-0.004**	-0.061
Year 2	**-0.325**	**-0.180**	**-0.035**	-0.186	-0.089	0.007	-1.019
				Imports			
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.050	0.018	0.087	-0.129	-0.032	0.064	0.842
Year -2	-0.046	0.020	0.085	-0.131	-0.041	0.050	1.056
Year 0	**-0.130**	**-0.084**	**-0.037**	**-0.080**	**-0.037**	**0.006**	-1.460
Year 1	**-0.205**	**-0.133**	**-0.061**	**-0.134**	**-0.074**	**-0.015**	-1.230
Year 2	**-0.288**	**-0.192**	**-0.095**	**-0.156**	**-0.085**	**-0.015**	-1.733

Notes: Lower bound and upper bound estimates made with 95% confidence intervals. Bold numbers indicate statistical significance at this level. T-statistics assume infinite degrees of freedom and are calculated using a one-tailed test ($\hat{\alpha}_d^H - \hat{\alpha}_d^L$). There are an average of 957 and 992 observations per estimated treatment effect for the high– and low–corruption groups, respectively. All estimations include a country-specific time trend.

The results suggest that the FCPA can discourage investment by preventing corrupt public officials from receiving rents. What is more interesting, however, is that there seems to be some recouping of losses among the high-corruption group. That is, rents (corruption perceptions) do not seem to decrease, while the decrease in investment and exports is accompanied by a decrease in imports, such that total economic activity (GDP per capita) remains unchanged. In contrast, it appears that low–corruption countries are less able to recoup losses – their GDP and all of the components fall after FCPA enforcement.

While there could be other mechanisms by which lost rents and economic activity are recouped after anti-corruption efforts, we put forth a particular hypothesis. If anti-corruption becomes more focused on legal markets, might not this encourage more rent-seeking in illegal markets? Could it thus be that FCPA enforcement induces corrupt public officials to recover lost bribe rents from (legal) investment contracts by extracting more bribes from illegal producers in exchange for allowing more illegal activity? In fact, might the decrease in imports that appear to offset the fall in investments in the high–corruption group be due to an increase in the underreporting of imports? That such anomaly is associated with trade-misinvoicing and, thus, illegal economic activity is indeed suggestive of our hypothesis of bribe-switching between legal and illegal markets. We test this hypothesis in the next section.

4 Growth in Illegal Markets

Does the FCPA, which is enforced against legal entities, induce corrupt public officials to switch to more bribe-taking from illegal markets? If so, we should expect illegal markets to grow since, in exchange for larger bribe payments, public officials have to decrease enforcement against illegal producers. This should be more apparent in countries in which public officials are already taking bribes from both legal and illegal sectors – that is, when the entire rent-seeking apparatus already enables such widespread corruption. In this case, it would be less costly for public officials to adjust their relative intensity of bribe-taking between the two sectors. In contrast, when the rent-seeking apparatus is limited to the legal sector, it might not be feasible for public officials to suddenly start taking bribes from illegal producers.

To test this bribe-switching hypothesis, we compare the effect of FCPA enforcement on the illegal markets of countries whose public officials are more likely, with those whose public officials are less likely, to be already extracting bribes from both legal and illegal markets. To do so, we first group the countries in the same manner as in Section 3 – according to initial corruption levels. However, a more direct way of ascertaining whether public officials are likely to extract bribes from illegal producers may be to group the countries according to the initial size of their shadow economy (as percentage of GDP), which is a measure of underground transactions. Since relatively more rents can be extracted from a large, rather than a small, shadow economy, one would expect that public officials are more likely to engage in bribe-taking in a large, rather than a small, shadow economy.[24] Thus, they would be more able to increase bribe-extraction from illegal producers when legal sources of rents dry out.

Our main measure for the size of illegal markets is the size of the shadow economy as percentage of GDP, as constructed by Medina and Schneider (2019). We expect that the shadow economies of countries with initially larger shadow economies increase more than those with initially smaller shadow economies. While the shadow economy measure of Medina and Schneider (2019) is constructed to focus on underground transactions, such transactions may involve both legal and illegal (i.e. prohibited) goods and services. We therefore also use other proxies for illegal activities, although data for these are limited. One

[24]The values of the bribe payments that have been subject to FCPA enforcement are very large – an average of $47 million per case from 1998–2019. Such amounts can be more easily recouped from large, rather than small, illegal markets.

proxy is homicide rates, as homicides and other crimes increase with a rise in drug trafficking and other illegal enterprise. Another is tree loss (as a percentage of total hectares), which can capture illegal logging. Finally, we have even sparser data on trade-misinvoicing – a measure that includes the under-reporting of imports to avoid customs duties.[25]

4.1 The Shadow Economy

Table 7 and Figure 6 suggest that FCPA enforcement increases the shadow economy of countries, irrespective of initial corruption levels. However, consistent with our bribe-switching hypothesis, the point estimates are generally higher for the high-corruption group. (The exception is in year 2, for which the point estimate for the low-corruption group is higher. However, years 3 through 5 see significant increases in the size of the shadow economy for the high-corruption group whereas the trend levels out and even starts falling in the low-corruption group (see Figure 6)).

After normalization of estimated coefficients, the results show that one FPCA case induces a nearly 0.28 percentage point (pp) increase in the shadow economy of the high-corruption group in year 0 and a 0.23 pp increase in year 1. In contrast, the shadow economies of low-corruption countries increase by 0.18 pp in year 0 and 0.17 pp in year 1.[26].

How large are these magnitudes relative to the bribe rents? A 0.28 pp increase is roughly equivalent to an average of $213 million of additional transactions in the underground economy of the average country in the high-corruption group.[27] The average amount of bribe

[25]Global Financial Integrity defines trade misinvoicing as "a method for moving money illicitly across borders which involves the deliberate falsification of the value, volume, and/or type of commodity in an international commercial transaction of goods or services by at least one party to the transaction...By under-reporting the value of goods, importers are able to immediately evade substantial customs duties or other taxes." See https://gfintegrity.org/issue/trade-misinvoicing/.

[26]Normalized coefficients for estimates presented in this section are given in Appendix A Tables A2 and A3

[27]The average country in this subsample has GDP equal to $200 billion and a shadow size of 38%, implying a shadow economy worth $76 billion. A 0.28 pp increase from this amount is equal to approximately $213

payments in FCPA cases involving countries in this group is $4.3 million, which is 2% percent of the growth in the shadow economy. In contrast, a 0.18 pp increase in the shadow economy of the low-corruption group is equivalent to $200 million, while the average bribe payments in FCPA cases involving these countries is $3.5 million.[28] Thus, the bribe payments constitute only 1.75% of the growth in the shadow economy of this group. Such patterns are consistent with our bribe-switching hypothesis, as the extent of rent-seeking from illegal markets should be larger in the high-corruption group.

Table 7: Dynamic Effect of Corruption Enforcement on the Size of the Shadow Economy - C&D (2020a) Estimator for the for the High–Corruption versus Low–Corruption Groups

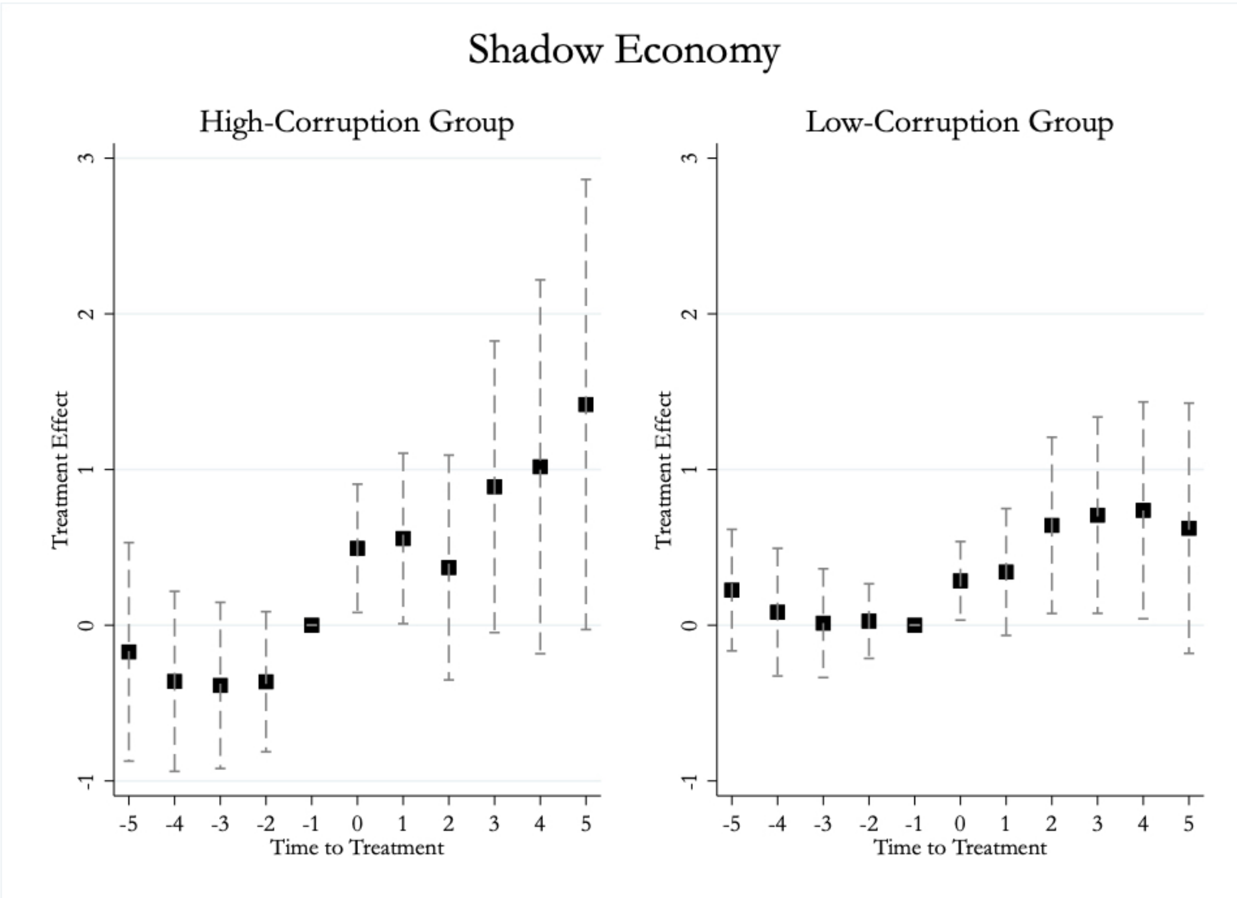
Percentiles	High–Corruption 0 - 50			Low–Corruption 50 - 100			Difference?
	LB	Coefficient	UB	LL	Coefficient	UB	T-Stat
Year -3	-0.921	-0.387	0.147	-0.336	0.013	0.363	-1.229
Year -2	-0.813	-0.363	0.087	-0.213	0.027	0.266	-1.498
Year 0	**0.082**	**0.494**	**0.906**	**0.033**	**0.285**	**0.537**	0.847
Year 1	**0.010**	**0.557**	**1.105**	-0.066	0.342	0.749	0.619
Year 2	-0.351	0.371	1.093	**0.075**	**0.642**	**1.208**	-0.579

Notes: Lower bound and upper bound estimates made with 95% confidence intervals. Bold rows and t-statistics are statistically significant at this 5% level. T-statistics assume infinite degrees of freedom and are calculated using a one-tailed test ($\hat{\alpha}_d^H - \hat{\alpha}_d^L$). There are an average of 900 and 897 observations per estimated treatment effect for the high–corruption group and low–corruption group, respectively. All estimations include a country-specific time trend.

million.

[28]The average country in this subsample has GDP equal to $481 billion and a shadow size of 23%, implying a shadow economy worth $111 billion. A 0.18 pp increase from this amount is equal to approximately $200 million.

Figure 6: Dynamic Effect of FCPA Enforcement on Shadow Economy Size for the High-Corruption Group (50th percentile or below) and Low-Corruption Group (greater than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

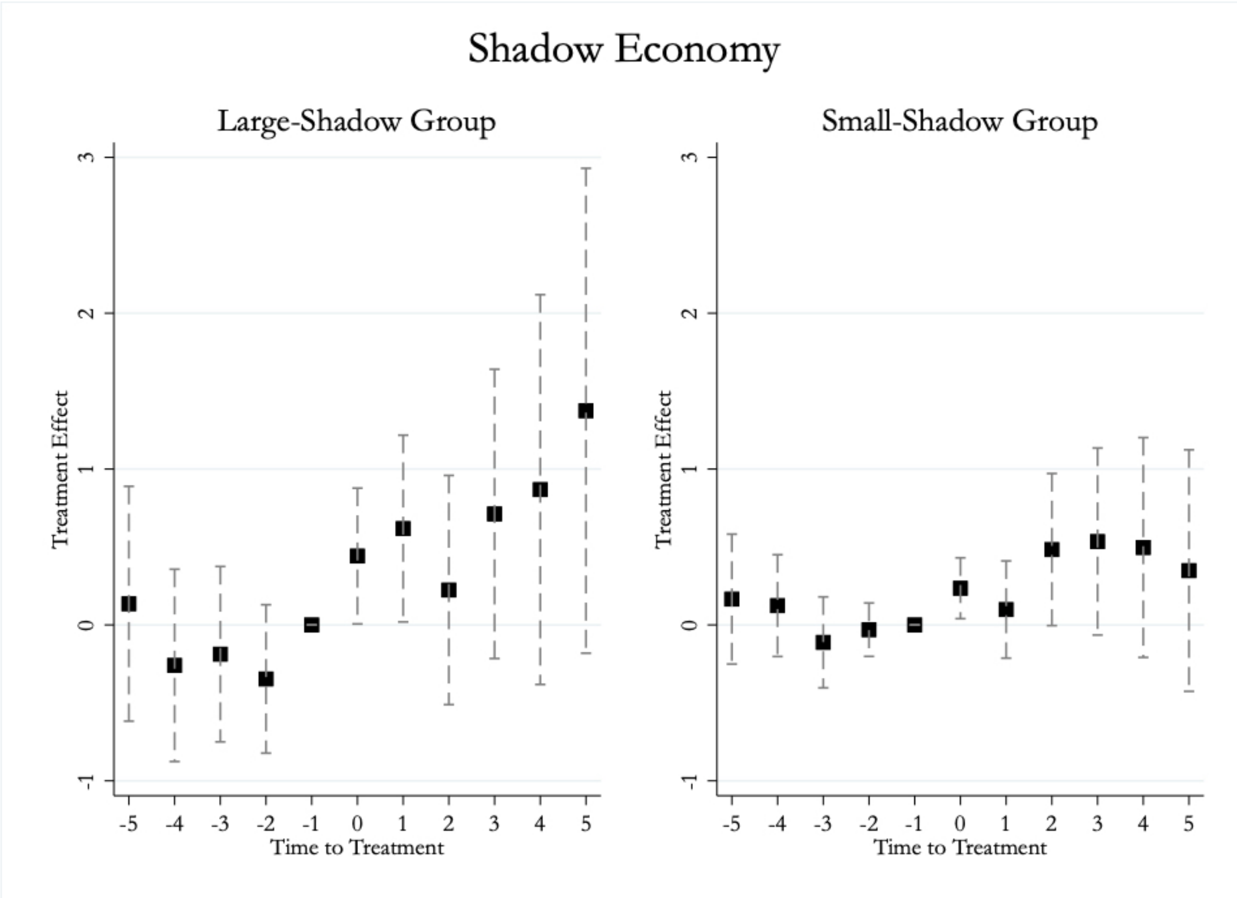
A similar trend emerges when we subset the sample according to the initial size of the shadow economy. Table 8 (top panel) and Figure 7 split the sample evenly – with countries in the 50th percentile and above (large-shadow economy group) having an initial (pre-1998) shadow economy that is at least 34 percent of its GDP. The point estimates for the large-shadow group are higher in years 0 and 1, but again lower in year 2. However, only the estimate for year 0 for the large-shadow group is statistically significant — one FCPA case induces a 0.15 pp increase in their shadow economy (Table A3).

Table 8: Dynamic Effect of Corruption Enforcement on the Size of the Shadow Economy - C&D (2020a) Estimator for Large–Shadow versus Small–Shadow Groups

	Large–Shadow Group			Small–Shadow Group			Difference?
Percentiles		50 - 100			0 - 50		
	LB	Coefficient	UB	LL	Coefficient	UB	T-Stat
Year -3	-0.750	-0.188	0.375	-0.404	-0.112	0.180	-0.234
Year -2	-0.823	-0.347	0.13	-0.202	-0.031	0.141	-1.224
Year 0	**0.006**	**0.442**	**0.878**	**0.04**	**0.235**	**0.431**	0.849
Year 1	**0.019**	**0.618**	**1.217**	-0.213	0.099	0.411	1.508
Year 2	-0.512	0.224	0.959	-0.004	0.483	0.971	-0.577
	Large–Shadow Group			Small–Shadow Group			Difference?
Percentiles		25 - 100			0 - 25		
	LB	Coefficient	UB	LL	Coefficient	UB	T-Stat
Year -3	-0.589	-0.179	0.231	**-0.725**	**-0.368**	**-0.012**	0.684
Year -2	-0.571	-0.253	0.065	-0.377	-0.115	0.147	-0.656
Year 0	**0.061**	**0.399**	**0.736**	-0.008	0.309	0.626	0.379
Year 1	**0.056**	**0.511**	**0.965**	-0.294	0.213	0.719	0.859
Year 2	-0.073	0.498	1.070	-0.498	0.171	0.840	0.729

Notes: Lower bound and upper bound estimates made with 95% confidence intervals. Bold rows and t-statistics are statistically significant at this 5% level. T-statistics assume infinite degrees of freedom and are calculated using a one-tailed test $(\hat{\alpha}_d^H - \hat{\alpha}_d^L)$. There are an average of 995 and 872 observations per estimated treatment effect for the large–shadow (50%) group and small–shadow (50%) group and an average of 1,058 and 320 large–shadow (25% or above) group and small–shadow (below 25%) group, respectively. All estimations include a country-specific time trend.

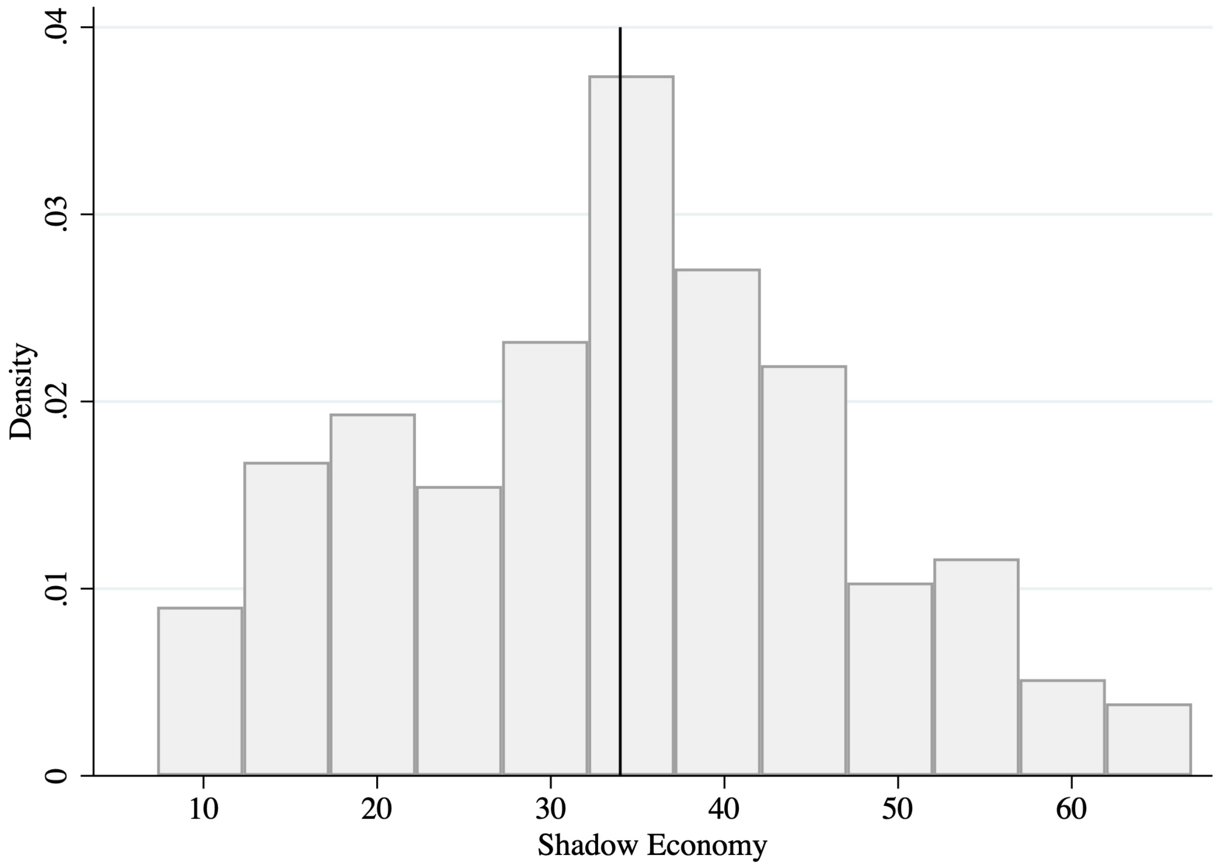
Figure 7: Dynamic Effect of FCPA Enforcement on Shadow Economy Size for the Large-Shadow Group (50th percentile or above) and Small-Shadow Group (less than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

That the point estimates in year 2 are higher for the small-shadow economy group appears puzzling, as it seems to suggest that there could be more bribe-switching in countries where it is relatively harder to extract bribes from the shadow economy to begin with. Note, however, that because of the 50-50 split of the sample, the small-shadow economy group actually has many countries with a shadow economy that is between 24-34 percent of their GDP – an arguably large percentage. (See Figure 8.) In fact, the small-shadow economy group actually includes countries such as Argentina (25.65%), Poland (28.6%), and Romania (31.23%). A likely reason for this is that the composition of the shadow economy can vary across countries – in some the measure might more intensely capture transactions involving prohibited goods and services, while in others it might consist largely of unreported incomes from *legal* goods and services.

Figure 8: Histogram of Average Shadow Economy Sizes pre-1998

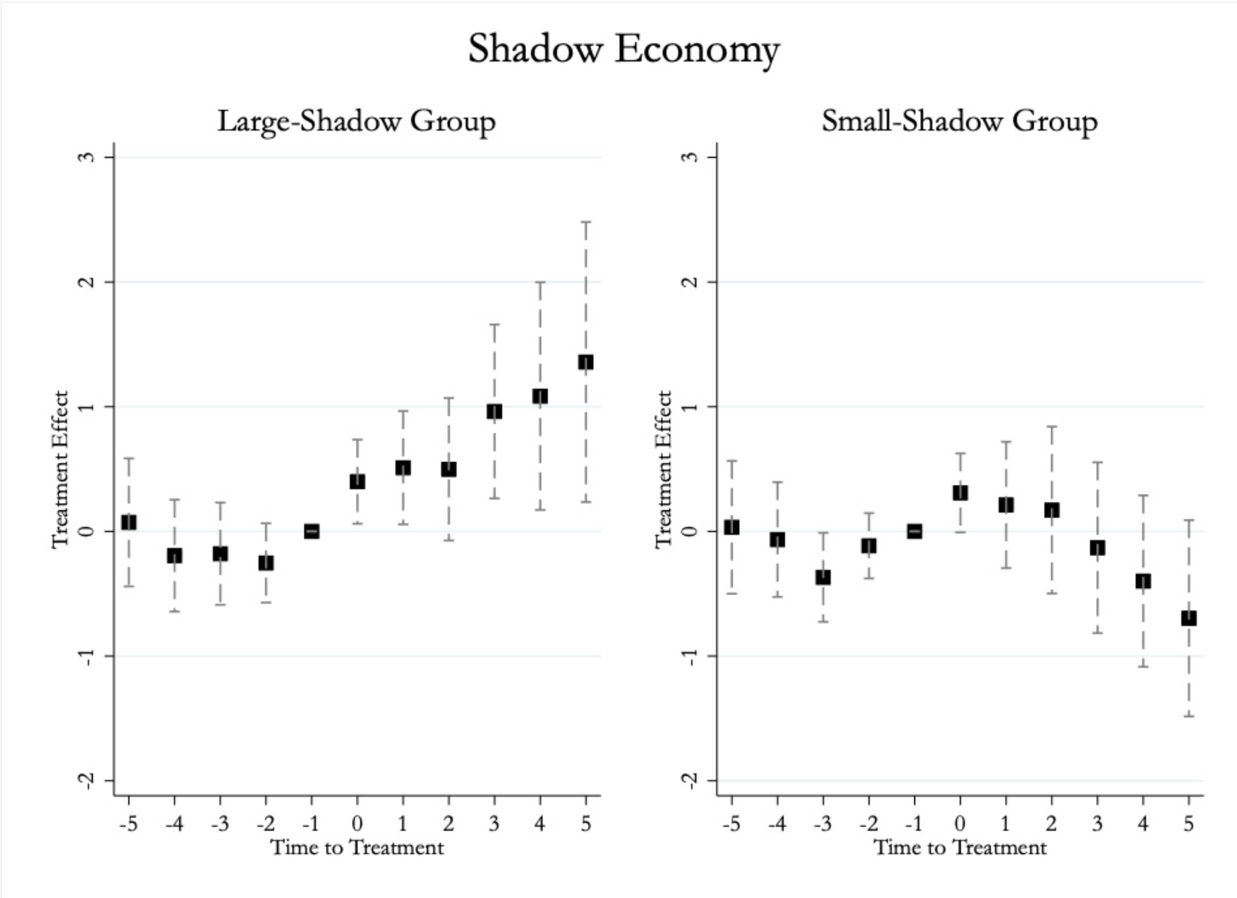


Notes: Bars correspond to 95% confidence intervals.

Thus, as an alternative, we also split the sample by grouping countries into the top 75th and bottom 25th percentile of initial shadow economy sizes, where the 75th percentile is 24 percent of GDP. Thus, only countries whose shadow economies are below 24 percent of GDP are included in the small-shadow economy group.[29] Table 8 (bottom panel) and Figure 9 now show that the point estimates for all post-treatment years are larger for the large-shadow group.

[29]For a list of these countries, see Table G1 in Appendix D. This refined small-shadow economy group still includes China and Iran. For robustness, we also try excluding these countries finding nearly identical results. These tables and figures are available upon request.

Figure 9: Dynamic Effect of FCPA Enforcement on Shadow Economy Size for the Large-Shadow Group (25th percentile or above) and Small-Shadow Group (less than the 25th percentile)



Notes: Bars correspond to 95% confidence intervals.

4.2 Other proxies for illegal activities

We consider other proxies for illegal activities. The disadvantage, however, is that we lose many observations, as the data on these proxies are limited. For brevity, we consider the effects of FCPA enforcement using our 50–50 sample splits only. Results using the 25–75 shadow-economy split are available upon request.[30] The top and middle panels of Tables 9 and 10 report treatment effects on homicide rates and tree loss. Consistent with our hypothesis, the point estimates, although imprecisely estimated, are generally larger for the

[30]Given the sparsity of this data, the results using the 25–75 split are extremely imprecise.

large-shadow economy group.

Table 9: Dynamic Effect of Corruption Enforcement on Other Illegal Activity - C&D (2020a) Estimator for the High–Corruption versus Low–Corruption Groups

	High–Corruption			Low–Corruption			Difference?
Percentiles		0 - 50			50 - 100		
			Homicide Rates				
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.084	-0.023	0.038	-0.040	0.013	0.066	-0.881
Year -2	-0.041	0.008	0.057	-0.053	-0.009	0.034	0.502
Year 0	-0.041	0.016	0.073	-0.051	-0.012	0.027	0.807
Year 1	-0.028	0.028	0.083	-0.084	-0.024	0.037	1.223
Year 2	-0.090	0.002	0.094	-0.113	-0.024	0.066	0.393
			Tree Loss				
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.020	0.011	0.043	-0.011	0.016	0.043	-0.213
Year -2	-0.009	0.013	0.034	-0.010	0.017	0.044	-0.252
Year 0	**0.002**	**0.049**	**0.096**	-0.017	0.038	0.094	0.286
Year 1	**0.005**	**0.048**	**0.091**	-0.022	0.013	0.048	1.231
Year 2	**0.003**	**0.062**	**0.121**	-0.030	0.006	0.042	1.590
			Trade Misinvoicing				
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-3.644	-0.535	2.574	-3.463	0.074	3.610	-0.253
Year -2	-2.227	-0.489	1.250	-5.059	-2.140	0.779	0.953
Year 0	-2.783	-0.258	2.266	-9.425	-1.564	6.296	0.310
Year 1	-3.677	0.054	3.784	-7.547	-1.298	4.951	0.364
Year 2	-3.006	1.728	6.461	-6.781	0.364	7.510	0.312

Notes: Lower bound and upper bound estimates made with 95% confidence intervals. Bold rows and t-statistics are statistically significant at this 5% level. T-statistics assume infinite degrees of freedom and are calculated using a one-tailed test ($\hat{\alpha}_d^H - \hat{\alpha}_d^L$). For homicide rates, there are an average of 567 and 936 observations per estimated treatment effect for the high–corruption group and low–corruption group, respectively. Likewise, there are an average of 226 and 113 observations for trade misinvoicing and 742 and 420 observations for the tree loss. All estimations include a country-specific time trend.

Table 10: Dynamic Effect of Corruption Enforcement on Other Illegal Activity - C&D (2020a) for the Large–Shadow (50^{th} percentile or above) versus Small–Shadow Groups (less than the 50^{th} percentile)

	Large–Shadow Group			Small–Shadow Group			Difference?
Percentiles		50 - 100			0 - 50		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Homicide Rates			
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.111	-0.033	0.044	-0.041	0.002	0.045	-0.776
Year -2	-0.066	0.000	0.065	-0.027	0.011	0.049	-0.288
Year 0	-0.046	0.017	0.081	-0.046	-0.006	0.034	0.604
Year 1	-0.026	0.043	0.113	-0.079	-0.023	0.033	1.463
Year 2	-0.094	0.009	0.111	-0.111	-0.030	0.050	0.589
				Tree Loss			
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-0.023	0.010	0.043	-0.001	0.023	0.048	-0.643
Year -2	-0.011	0.015	0.041	-0.006	0.018	0.042	-0.148
Year 0	**0.003**	**0.057**	**0.111**	-0.016	0.032	0.079	0.688
Year 1	**0.006**	**0.052**	**0.098**	-0.007	0.029	0.066	0.756
Year 2	**0.003**	**0.066**	**0.129**	-0.013	0.032	0.076	0.864
				Trade Misinvoicing			
	LB	Coefficient	UB	LB	Coefficient	UB	T-Stat
Year -3	-3.409	-0.695	2.018	-2.427	1.289	5.005	-0.845
Year -2	-2.216	-0.808	0.600	-2.085	-0.201	1.683	-0.506
Year 0	-2.422	0.276	2.974	-3.312	-0.607	2.098	0.453
Year 1	-3.398	0.536	4.470	-4.613	-0.627	3.358	0.407
Year 2	-2.478	2.311	7.100	-5.784	-0.057	5.670	0.622

Notes: Lower bound and upper bound estimates made with 95% confidence intervals. Bolded rows and t-statistics are statistically significant at this 5% level. T-statistics assume infinite degrees of freedom and are calculated using a one-tailed test ($\hat{\alpha}_d^H - \hat{\alpha}_d^L$). For homicide rates, there are an average of 560 and 690 observations per estimated treatment effect for the large–shadow group and small–shadow group, respectively. Likewise, there are an average of 253 and 86 observations for trade misinvoicing and 623 and 427 observations for the tree loss, respectively. All estimations include a country-specific time trend.

Tree loss in particular seems to increase significantly in initial high-corruption countries. One FCPA enforcement case increases tree loss (as a percentage of hectacers) by 0.027 pp in year 0, 0.019 pp in year 1, and 0.020 pp in year 2. Given that the average loss in any given year is only 0.181 pp, these are substantial effects. Further, as will be discussed in the following section, despite the limited data these estimates are remarkably consistent across the five different estimators employed in the paper.

Trade misinvoicing is our most limited measure in terms of data availability. Still, we find that it generally increases for the high-corruption or large-shadow group and decreases for the low-corruption or small-shadow group. While imprecisely estimated, these results are nevertheless supportive of our bribe-switching hypothesis. Recall that FCPAenforcement decreases imports, more so for countries with initially higher levels of corruption. The results on trade misinvoicing suggest that this might be indicative of an increase in the under-reporting of imports.

4.3 Robustness Checks

Recall that our reported results have been obtained using the de Chaisemartin and D'Haultfœuille (2020a) estimator with a country-specific time trend. For robustness, we also run the regressions using other estimators: TWFE, the Callaway and SantâAnna (2020) estimator with never treated units as counterfactuals, a stacked difference-in-difference estimator a la Cengiz et al. (2019), the de Chaisemartin and D'Haultfœuille (2020a) estimator without the country-specific time trend. The results from these are summarized in Appendix C.

Two interesting patterns emerge when comparing estimators. First, the country-specific time trend appears to be very important in our model. Figure B1 suggests that the high-corruption group has a pre-existing trend present when utilizing TWFE or stacked estimates. Though less extreme, this trend is also present in the Callaway and SantâAnna (2020) results and the de Chaisemartin and D'Haultfœuille (2020a) results without the country specific time trend. The trend entirely disappears once it is incorporated in the latter. Second, our key finding - that illicit activity rises in the high-corruption and/or large-shadow group - is generally consistent across all five estimators. As shown in Figure B9, the estimates track closely in both the pre-and-post treatment period. The same is true for Figure B10. While there is some discrepancy in our other key findings - that investment, exports, and imports fall - the results are consistent across both de Chaisemartin and D'Haultfœuille (2020a) estimates and the Callaway and SantâAnna (2020) estimates. It is the TWFE and stacked estimates that show some divergence, the former of which is to be expected.

We conduct a series of other robustness checks. For brevity, we report these for our measures of illicit activity. Results for the other measures are available upon request. First, we estimate the treatment effects for the subsample of countries involved in FCPA cases that were filed by the DOJ (Appendix C), and for the subsample involved in cases filed by the SEC (Appendix D).[31] This is to see whether there might be patterns of political targeting of certain countries. Such targeting should be less apparent in cases filed by the SEC, as the SEC is independent of the US federal government. The results from each of these subsamples follow the same patterns as those obtained using the main sample (reported in Sections 3 and 4), although they are generally stronger for DOJ cases.

Second, recall that in order to focus on the effect of the 1998 FCPA reform, we assign a value of 0 to the treatment variable in the years 1990 to 1997. However, there are a few cases in this period. For robustness, we thus exclude from the sample the countries that had at least one FCPA case between 1990 and 1997. As shown in Appendix F, the results are again very similar. Illicit activity increases more amongst the high–corruption group than the low–corruption group.

Finally, we conduct a placebo test by randomly *re*assigning the treatment across countries. That is, for each country, we assign it treatment values from another country in our

[31] These appendices summarize the results using a graph. We also provide tables summarizing the two-year estimates in Online Appendix 2.

sample chosen at random. As a hypothetical example, we take the treatment values of Brazil from 1990–1999 and assign these values to Russia. We do this for all countries, and re-run the regressions to estimate the effect of these 'false' treatments. Then we repeat this procedure many times to get standard errors of the estimates. We find that such estimates hover around zero, which helps allay endogeneity concerns with FCPA enforcement.[32]

5 Conclusion

The US Foreign Corrupt Practices Act (FCPA) is a major piece of legislation that enforces against US and non-US entities that are involved in paying bribes to foreign public officials. Its expanded version – the post-1998 reform, embodies a commitment to the 1997 OECD Anti-Bribery Convention that establishes anti-bribery as a binding legal principle in the international sphere.

We find an adverse, unintended consequence of the FCPA. Foreign countries whose public officials have been involved in bribe-taking from firms and entities subject to the FCPA experience a growth in illegal markets. We posit that the FCPA, by decreasing bribe-taking opportunities from the legal sector, e.g. investment contracts, induces corrupt public officials to switch their bribe-taking to illegal markets in order to recover lost rents. In exchange for these bribes, officials enforce less against illegal producers, enabling the growth of illegal activities. We find that one FCPA case alone increases the foreign country's shadow economy by as much as 0.28 percentage points (pp), its tree loss by 0.027 pp, and its trade misinvoicing by 0.5 pp.

[32]Due to the volume of results, we have not included them in the Appendix; however, we can provide them upon request.

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Appendices

A A Model of Bribe-Switching

We model bribe-taking as menu auctions a la Grossman and Helpman (1994, 2001), Bernheim and Whinston (1986a,b) and Dixit et al. (1997) in which firms pay public officials bribes in exchange for their preferred policy, e.g. the allocation of government revenues. The framework thus far has been used to model bribery in legal markets, and our innovation is to include bribery in illegal markets. We follow Becker et al. (2006) and Desierto and Nye (2017) in which illegal producers pay bribes to avoid getting caught producing their goods. The problem of the government is, thus, how to allocate government revenues between these markets. Revenues are spent on (ordinary) public spending, e.g. public works contracts, that benefit legal firms but not illegal ones, and law enforcement spending that enforces against corruption and illegal-good production. Total public spending benefits legal firms in varying degrees, depending partly on how much is targeted towards them. These firms thus pay bribes in order to get a larger share of total public spending. Similarly, law enforcement spending affects illegal firms in varying degrees, depending partly on how much is targeted towards them. These firms thus pay bribes in order to get a smaller share of total law enforcement spending which, in effect, allows them to better avoid detection and prosecution.

Consider, then, an economy consisting of legal and illegal markets, with L legal producers and $\neg L$ illegal producers. The incumbent government I has discretion over the use of government revenues $T + R$, where T denotes tax revenues and R windfall revenues, e.g. from oil and natural resources. It can allocate these revenues between public spending g_L that increases the productivity of legal markets but which illegal producers cannot access, and law enforcement spending $g_{\neg L}$ which positively affects legal producers, but negatively affects illegal producers. In particular, the benefit of a legal producer $i \in \{L\}$ is $V_i(g_{Li}, g_{\neg L})$, with $\frac{\partial V_i(\cdot)}{\partial g_{Li}} > 0$, $\frac{\partial V_i(\cdot)}{\partial g_{\neg L}} > 0$, $\frac{\partial^2 V_i(\cdot)}{\partial g_{Li}^2} < 0$, $\frac{\partial^2 V_i(\cdot)}{\partial g_{\neg L}^2} < 0$, and g_{Li} denoting the proportion of total public spending g_L that is allocated to i. Let i index relative productivity such that $V_1(g_L, g_{\neg L}) > V_2(g_L, g_{\neg L}) > ...V_L(g_L, g_{\neg L}) \; \forall \; g_L \in (0, (T+R-g_{\neg L})]$ and $g_{\neg L} \in (0, (T+R-g_L)]$. That is, producer 1 is the most productive among all legal producers. Meanwhile, the benefit of an illegal producer $j \in \{\neg L\}$ is $V_j(g_{\neg Lj})$, with $\frac{\partial V_j(\cdot)}{\partial g_{\neg Lj}} < 0$, $\frac{\partial^2 V_j(\cdot)}{\partial g_{\neg Lj}^2} > 0$, and $g_{\neg Lj}$ denoting the proportion of total enforcement spending $g_{\neg L}$ that is allocated or targeted towards j. Similarly, let j index relative productivity such that $V_1(g_{\neg L}) > V_2(g_{\neg L}) > ...V_{\neg L}(g_{\neg L}) \; \forall \; g_{\neg L} \in (0, (T + R - g_L)]$. That is, illegal producer 1 is the most resilient producer, as it is least adversely affected by enforcement.

The incumbent can extract bribes from legal and illegal producers. Producer $i \in \{L\}$ can offer bribe b_i in exchange for proportion g_{Li} of public spending – which i wants to be as large as possible, while illegal producer $j \in \{\neg L\}$ can offer bribe or protection money b_j in exchange for proportion $g_{\neg Lj}$ of enforcement spending – which j wants to be as small as possible.

Producer $i \in \{L\}$ pays bribe offer b_i, provided it is not caught bribing, while illegal producer $j \in \{\neg L\}$ pays bribe offer b_j provided it not caught producing illegal goods in the first place. Letting ρ_L denote the probability of getting caught bribing in the legal sector, and $\rho_{\neg Lj}$ the probability that j is caught producing illegal goods, producer i's expected benefit is thus $V_i(g_{Li}, g_{\neg L}) - (1 - \rho_L)b_i$, while j's expected benefit is $(1 - \rho_{\neg Lj})[V_j(g_{\neg Lj}) - b_j]$.

In turn, assume that ρ_L depends on total enforcement spending $g_{\neg L}$, while $\rho_{\neg Lj}$ depends on the particular proportion $g_{\neg Lj}$ of enforcement spending that is targeted towards j. Specifically, let $\rho_L \equiv \rho_L(\bar{\rho}_L, g_{\neg L})$, $\frac{\partial \rho_L(\cdot)}{\partial \bar{\rho}_L} > 0$, $\frac{\partial \rho_L(\cdot)}{\partial g_{\neg L}} > 0$, $\frac{\partial^2 \rho_L(\cdot)}{\partial \bar{\rho}_L^2} < 0$, $\frac{\partial^2 \rho_L(\cdot)}{\partial g_{\neg L}^2} < 0$, with $\bar{\rho}_L$ capturing other factors affecting the probability of getting caught bribing in legal markets that are exogenous to the model. Let $\rho_{\neg Lj} \equiv \rho_{\neg L}(\bar{\rho}_{\neg L}, g_{\neg Lj})$, $\frac{\partial \rho_{\neg Lj}(\cdot)}{\partial g_{\neg L}} > 0$, $\frac{\partial \rho_{\neg Lj}(\cdot)}{\partial g_{\neg Lj}} > 0$, $\frac{\partial^2 \rho_{\neg Lj}(\cdot)}{\partial g_{\neg L}^2} < 0$, $\frac{\partial^2 \rho_{\neg Lj}(\cdot)}{\partial g_{\neg Lj}^2} < 0$, with $\bar{\rho}_{\neg L}$ capturing exogenous determinants of the probability of detecting illegal production.

Finally, the incumbent derives utility from both the bribe-rents and social welfare, but only considers welfare from legal production. In particular, let its utility U_I be equal to $\alpha\Big[\sum_i V_i(g_{Li}, g_{\neg L})\Big] + (1-\alpha)\Big[\sum_i(1-\rho_L)b_i + \sum_j(1-\rho_{Lj})b_j\Big]$, with the first term in square brackets as total social welfare and the second term total expected bribe-rents, and with α denoting the extent to which I cares about social welfare, and thus capturing institutional checks and balances, and the strength of political competition, that limit the rent-seeking of I.

Consider the following two-stage game.

1. Incumbent I chooses how to allocate revenues $T + R$ between public spending g_L and enforcement spending $g_{\neg L}$.

2. Each legal producer $i \in \{L\}$ offers I bribe b_i in exchange for proportion g_{Li} of public spending. Each illegal producer $j \in \{\neg L\}$ offers I bribe b_j to avoid proportion $g_{\neg Lj}$ of enforcement spending.

By backward induction, one can characterize the amount of bribes paid by each legal and illegal producer in equilibrium, as well as the amount of public good spending allocated to each $i \in \{L\}$ and enforcement spending allocated to each $j \in \{\neg L\}$, and the equilibrium allocation of total revenues between (total) public spending and (total) enforcement spending.

A.1 Rents and Public Spending in Legal Markets

We first solve for equilibrium bribes from, and the allocation of public spending among, legal producers. In the second stage of the game, total public spending g_L is fixed, and each legal producer i offers bribe i in order to get the highest proportion of g_L possible. Denote as $-i$ a legal producer that is not producer i. The equilibrium amount of the bribe from, and allocation to, producer i are jointly efficient for i and the bribe-taker I and, hence, are obtained by solving the following optimization problem for each $i \in \{L\}$:

$$Max_{g_{Li},b_i} V_i(g_{Li}, g_{\neg L}) - (1-\rho_L)b_i$$
$$s.t.\ g_{Li} + \sum_{-i} g_{L-i} = g_L\ (a)$$
$$\alpha\Big[V_i(g_{Li}, g_{\neg L}) + \sum_{-i} V_{-i}(g_{L-i}, g_{\neg L})\Big] + (1-\alpha)\Big[(1-\rho_L)b_i + \sum_{-i}(1-\rho_L)b_{-i} + \sum_j (1-\rho_{\neg Lj})b_j\Big] \geq \bar{U}_i\ (b),$$

where constraint (a) is the relevant budget constraint at this point in the game, which prescribes that total public spending g_L is to be entirely allocated to L producers, and constraint (b) is the incumbent's participation constraint, with $\bar{U}_i$ denoting the incumbent's reservation utility – the utility it would obtain if it does not accept the bribe offer of i.

To obtain an expression for $\bar{U}_i$, note that if the incumbent rejects the bribe, then she reallocates total public spending in a way that would maximize her utility without i's bribe, that is, setting $b_i = 0$. Denote such allocation as g^0_{Li}, g^0_{L-1}. Then, $\bar{U}_i = \alpha[V_i(g^0_{Li}, g_{\neg L}) + \sum_{-i} V_{-i}(g^0_{L-i}, g_{\neg L})] + (1-\alpha)[\sum_{-i}(1-\rho_L)b_{-i} + \sum_j(1-\rho_{Lj})b_j]$. Constraint (b) then becomes $\alpha\Big[V_i(g_{Li}, g_{\neg L}) - V_i(g^0_{Li}, g_{\neg L}) + \sum_{-i}[V_{-i}(g_{L-i}, g_{\neg L}) - V_{-i}(g^0_{L-i}, g_{\neg L})]\Big] + (1-\alpha)(1-\rho_L)b_i \geq 0$. Letting this fully bind obtains an expression for b_i:

$$b_i = \max\left\{\frac{\alpha}{(1-\alpha)(1-\rho_L)} \sum_i [V_i(g^0_{Li}, g_{\neg L}) - V_i(g_{Li}, g_{\neg L})], 0\right\} \quad (4)$$

Thus, for producer i to pay positive bribe $b_i > 0$, it must be that $\sum_i[V_i(g^0_{Li}, g_{\neg L}) - V_i(g_{Li}, g_{\neg L})] > 0$. That is, the bribe compensates the incumbent for the fraction $\frac{\alpha}{(1-\alpha)(1-\rho_L)}$ of the loss of total social benefit from allocating total public spending as g_{Li}, g_{L-i}, rather than g^0_{Li}, g^0_{L-i}.[33] Note that b_i is the same across producers since each i has the same probability ρ_L of being enforced against for bribery.

[33]This does not require $V_i(g^0_{Li}, g_{\neg L} - V_i(g_{Li}, g_{\neg L}) > 0$ or that $g^0_{Li} > g_{Li}$ for each i.

Plugging (4) into the maximand obtains the following Kuhn Tucker conditions, where $\lambda > 0$ is the value of the Lagrange multiplier assuming constraint (a) fully binds:

$$\left(\frac{1}{1-\alpha}\right)\frac{\partial V_i}{\partial g_{Li}} + \lambda = 0 \tag{5}$$

$$\lambda(g_L - g_{Li} - \sum_{-i} g_{L-i}) = 0 \tag{6}$$

Solving these conditions simultaneously, i.e. across all i, gives the optimal public spending g_{Li} for each i. Thus:

Proposition 1. *The most (least) productive legal producer obtains the lowest (highest) public spending, but pays the same bribe as the rest. That is, $g_{L1} < g_{L2} < ... < g_{LL}$ and $b_1 = b_2 = ... = b_L$.*

Proof. Condition (5) implies that (i) $\frac{\partial V_1}{\partial g_{L1}} = \frac{\partial V_2}{\partial g_{L2}} = ... = \frac{\partial V_L}{\partial g_{LL}}$. Since $V_1 > V_2 > ...V_L$ when each i is given the same allocation, then (i) cannot hold if $g_{L1} > g_{L2} > ... > g_{LL}$. As for bribes, equation (4) shows that b_i is identical across all i. □

A.2 Rents and Enforcement Spending in Illegal Markets

In illegal markets, bribe-taking is not the only activity that is enforced upon. An illegal producer j's entire enterprise, and therefore net benefit $V_j(g_{\neg Lj}) - b_j$, can only be obtained if the producer avoids enforcement, that is, with probability $1 - \rho_{\neg Lj}$.

As in legal markets, an illegal producer pays the bribe b_j in exchange for an allocation $g_{\neg Lj}$ out of total enforcement spending $g_{\neg L}$. The difference is that the illegal producer would want the allocation to be as small as possible, that is, it wants to minimize enforcement, as both $V_j(\cdot)$ and $(1 - \rho_{\neg Lj})$ are decreasing in $g_{\neg Lj}$.

Thus, for each illegal producer $j \in \{\neg L\}$, the optimal enforcement $g_{\neg Lj}$ and bribe b_j are obtained by solving:

$$Max_{g_{\neg Lj}, b_j}(1-\rho_{\neg Lj})[V_j(g_{\neg Lj}) - b_j]$$

$$s.t.\ g_{\neg Lj} + \sum_{-j} g_{\neg L-j} = g_{\neg L}\ (a)$$

$$\alpha\Big[\sum_i V_i(g_{Li}, g_{\neg L})\Big] + (1-\alpha)\Big[(1-\rho_{\neg Lj})b_j + \sum_{-j}(1-\rho_{\neg Lj})b_{-j} + \sum_i (1-\rho_L)b_i\Big] \geq \bar{U}_j\ (b)$$

To get an expression for the incumbent's reservation utility $\bar{U}_j$, note that if the incumbent rejects the bribe, she loses b_j but still enforces against j with some effort. That is, total enforcement spending $g_{\neg L}$ is reallocated among j such that the incumbent's utility without j's bribe is maximized. Denote such reallocation as $g^0_{\neg Lj}, g^0_{\neg L-j}$ $\forall (j,-j) \in \{\neg L\}$. The incumbent's reservation utility is thus $\bar{U}_j = \alpha[\sum_i V_i(g_{Li}, g_{\neg L})] + (1-\alpha)[\sum_{-j}(1-\rho^0_{\neg L-j})b_{-j} + \sum_i (1-\rho_L)b_i]$, where $\rho^0_{\neg L-j} \equiv \rho_{\neg L}(\bar{\rho}_{\neg L}, g^0_{\neg L-j})$. Constraint (b) then becomes $(1-\alpha)[(1-\rho_{\neg Lj})b_j + \sum_{-j}(\rho^0_{\neg L-j} - \rho_{\neg L-j})b_{-j}] \geq 0$. Letting this fully bind, one obtains the following expression for the minimum bribe that the incumbent is willing to accept from j:

$$b_j = \max\left\{\frac{1}{1-\rho_{\neg Lj}}\sum_{-j}(\rho_{\neg L-j} - \rho^0_{\neg L-j})b_{-j}, 0\right\} \tag{7}$$

Thus, for a producer j to pay bribe $b_j > 0$, it must be that the enforcement against other producers is such that $\sum_{-j}(\rho_{\neg L-j} - \rho^0_{\neg L-j}) > 0$. The intuition is that since an illegal producer bribes the incumbent in order to lower enforcement against it at the expense of other producers, the bribe from j precisely compensates the incumbent for a fraction $\frac{1}{1-\rho_{\neg Lj}}$ of the loss of expected bribes from other illegal producers due to the increased enforcement against them.

One can then plug (7) into the maximand and, together with constraint (a), obtain the following Kuhn-Tucker conditions for each $j \in \{\neg L\}$ with $\lambda > 0$ the value of the Lagrange multiplier when (a) fully binds:

$$(1-\rho_{\neg Lj})\Big[\frac{\partial V_j}{\partial g_{\neg Lj}} - (\frac{1}{1-\rho_{\neg Lj}})^2 \frac{\partial \rho_{\neg Lj}}{\partial g_{\neg Lj}} \sum_{-j} (\rho_{\neg Lj} - \rho^0_{\neg L-j}) b_{-j}\Big] \tag{8}$$

$$-\frac{\partial \rho_{\neg Lj}}{\partial g_{\neg Lj}} \Big[V_j(\cdot) - \frac{1}{1-\rho_{\neg Lj}} \sum_{-j} (\rho_{\neg L-j} - \rho^0_{\neg L-j}) b_{-j}\Big] + \lambda = 0$$

$$\lambda(g_{\neg L} - g_{\neg Lj} - \sum_{-j} g_{\neg L-j}) = 0 \tag{9}$$

Solving the conditions simultaneously, i.e. across all j, gives the optimal enforcement spending $g_{\neg Lj}$ for each j. Thus:

Proposition 2. *The most (least) resilient illegal producer incurs the lowest (greatest) enforcement and pays the smallest (highest) bribe. That is,* $g_{\neg L1} < g_{\neg L2} < ... < g_{\neg L\neg L}$ *and* $b_1 < b_2 < ... < b_{\neg L}$.

Proof. Consider condition (8) for producer 1 and 2, which yields

(i) $(1-\rho_{\neg L1})\Big[\frac{\partial V_1}{\partial g_{\neg L1}} - (\frac{1}{1-\rho_{\neg L1}})^2 \frac{\partial \rho_{\neg L1}}{\partial g_{\neg L1}} \sum_{-j\backslash 1} (\rho_{\neg L1} - \rho^0_{\neg L-j\backslash 1}) b_{-j\backslash 1}\Big] - \frac{\partial \rho_{\neg L1}}{\partial g_{\neg L1}} \Big[V_j(\cdot) - \frac{1}{1-\rho_{\neg L1}} \sum_{-j\backslash 1} (\rho_{\neg L-j\backslash 1} - \rho^0_{\neg L-j\backslash 1}) b_{-j\backslash 1}\Big]$

$= (1-\rho_{\neg L2})\Big[\frac{\partial V_2}{\partial g_{\neg L2}} - (\frac{1}{1-\rho_{\neg L2}})^2 \frac{\partial \rho_{\neg L2}}{\partial g_{\neg L2}} \sum_{-j\backslash 2} (\rho_{\neg L2} - \rho^0_{\neg L-j\backslash 2}) b_{-j\backslash 2}\Big] - \frac{\partial \rho_{\neg L2}}{\partial g_{\neg L2}} \Big[V_2(\cdot) - \frac{1}{1-\rho_{\neg L2}} \sum_{-j\backslash 2} (\rho_{\neg L-j\backslash 2} - \rho^0_{\neg L-j\backslash 2}) b_{-j\backslash 2}\Big]$. Suppose $g_{\neg L1} < g_{\neg L2}$. Then $V_1 > V_2$ which, in order for the condition (i) to be met, requires $\frac{\partial \rho_{\neg L1}}{\partial g_{\neg L1}} < \frac{\partial \rho_{\neg L2}}{\partial g_{\neg L2}}$ which, in turn, implies $g_{\neg L1} < g_{\neg L2}$. However, if $g_{\neg L1} \geq g_{\neg L2}$, it may still be the case that $V_1 > V_2$, in which case condition (i) requires $\frac{\partial \rho_{\neg L1}}{\partial g_{\neg L1}} < \frac{\partial \rho_{\neg L2}}{\partial g_{\neg L2}}$, which implies $g_{\neg L1} < g_{\neg L2}$, a contradiction. Thus, the condition is only always met when $g_{\neg L1} < g_{\neg L2}$.

As for bribes, equation (7) shows that b_j increases with $\rho_{\neg Lj}$, which is increasing in $g_{\neg Lj}$. Thus, if $g_{\neg L2} > g_{\neg L1}$, then $b_2 > b_1$. □

A.3 Allocation of Revenues Between Public Spending and Enforcement

Moving backward in the game, the incumbent maximizes utility $U_I = \alpha\Big[\sum_i V_i(g_{Li}, g_{\neg L})\Big] + (1-\alpha)\Big[\sum_i(1-\rho_L)b_i + \sum_j(1-\rho_{\neg Lj})b_j\Big]$, where $b_i, b_j, g_{Li}, g_{\neg Lj}\ \forall\ i \in \{L\}, j \in \{\neg L\}$ are the equilibrium values from the last stage of the game, and recall that $\rho_L \equiv \rho_L(\bar{\rho}_L, g_{\neg L})$ and $\rho_{\neg Lj} \equiv \rho_{\neg Lj}(\bar{\rho}_{\neg L} g_{\neg Lj})$, with $\bar{\rho}_L$ and $\bar{\rho}_{\neg Lj}$ capturing exogenous factors.

The budget constraint is $T + R = g_L + g_{\neg L}$. Re-writing this as $g_{\neg L} = T + R - g_L$, the incumbent solves

$$
\begin{aligned}
Max_{g_L}\alpha\Big[\sum_i V_i(g_{Li}, (T+R-g_L))\Big] \\
+(1-\alpha)\Big[\sum_i(1-\rho_L(\bar{\rho}_L, (T+R-g_L)))b_i \\
+\sum_j(1-\rho_{\neg Lj})b_j\Big].
\end{aligned}
$$

The equilibrium level of total public spending satisfies FOC $-\alpha\frac{\partial V_i(\cdot)}{\partial(T+R-g_L)} + (1-\alpha)\sum_i\frac{\partial \rho_L(\cdot)}{\partial(T+R-g_L)}b_i = 0$ or, with $T + R - g_L = g_{\neg L}$:

$$
\sum_i \frac{\partial V_i(\cdot)}{\partial g_{\neg L}} = \frac{1-\alpha}{\alpha}\sum_i \frac{\partial \rho_L(\cdot)}{\partial g_{\neg L}} b_i. \tag{10}
$$

Thus, revenues are allocated towards enforcement spending $g_{\neg L}$ in the amount that equates the marginal productivity of the legal market from such spending with a fraction $\frac{1-\alpha}{\alpha}$ of the marginal expected bribes that can be extracted from that market.

A.4 Corruption Enforcement Against Legal Producers

Anti-Corruption efforts in the legal market increase the probability $\bar{\rho}_L$ of getting caught bribing in the legal sector. In the following, we derive key comparative static results with respect to $\bar{\rho}_L$.

Proposition 3. *Provided that enforcement is sufficiently effective in the legal market — when $\frac{\partial \rho_L}{\partial g_{\neg L}}$ is sufficiently large and $|\frac{\partial^2 \rho_L}{\partial g_{\neg L}^2}|$ is sufficiently small, then in increase in $\bar{\rho}_L$, e.g. from FCPA enforcement, increases public spending g_L and decreases enforcement spending $g_{\neg L}$. That is, $\frac{\partial g_L}{\partial \bar{\rho}_L} > 0$ and $\frac{\partial g_{\neg L}}{\partial \bar{\rho}_L} < 0$.*

Proof. Re-write condition (10) as $F \equiv \frac{1-\alpha}{\alpha} \sum_i \frac{\partial \rho_L(\cdot)}{\partial g_{\neg L}} b_i - \sum_i \frac{\partial V_i(\cdot)}{\partial g_{\neg L}} = 0$, such that $\frac{\partial g_{\neg L}}{\partial \bar{\rho}_L} = -\frac{\partial F}{\partial \bar{\rho}_L} / \frac{\partial F}{\partial g_{\neg L}}$. Now, $-\frac{\partial F}{\partial \bar{\rho}_L} = \frac{1-\alpha}{\alpha} \frac{\partial \rho_L}{\partial g_{\neg L}} \sum_i \frac{\partial b_i}{\partial \bar{\rho}_L} < 0$ since ρ_L is increasing in $\bar{\rho}_L$ and, therefore, from (4), $\frac{\partial b_i}{\partial \bar{\rho}_L} > 0 \ \forall \ i \in \{L\}$. Meanwhile, $\frac{\partial F}{\partial g_{\neg L}} = \frac{1-\alpha}{\alpha} \left(\frac{\partial^2 \rho_L}{\partial g_{\neg L}^2} \sum_i b_i + \frac{\partial \rho_L}{\partial g_{\neg L}} \sum_i \frac{\partial b_i}{\partial g_{\neg L}} \right) - \sum_i \frac{\partial^2 V_i(\cdot)}{\partial g_{\neg L}^2}$. By assumption, $\frac{\partial^2 V_i(\cdot)}{\partial g_{\neg L}^2} < 0$ and $\frac{\partial^2 \rho_L}{\partial g_{\neg L}^2} < 0$, while (7) implies that $\frac{\partial b_i}{\partial g_{\neg L}} > 0$. (To see the latter, note that given $b_i > 0$, then $\sum_i V_i(g_{Li}^0, g_{\neg L}) > \sum_i V_i(g_{Li}, g_{\neg L})$, which implies $\frac{\partial \sum_i V_i(g_{Li}^0, g_{\neg L})}{\partial g_{\neg L}} > \frac{\partial \sum_i V_i(g_{Li}, g_{\neg L})}{\partial g_{\neg L}}$ and, therefore, $\frac{\partial b_i}{\partial g_{\neg L}} > 0$.) Thus, $\frac{\partial F}{\partial g_{\neg L}} > 0$ for as long as (i) $-\frac{1-\alpha}{\alpha} \frac{\partial^2 \rho_L}{\partial g_{\neg L}^2} < \frac{1-\alpha}{\alpha} \frac{\partial \rho_L}{\partial g_{\neg L}} \sum_i \frac{\partial b_i}{\partial g_{\neg L}} - \sum_i \frac{\partial^2 V_i}{\partial g_{\neg L}^2}$. Note that condition (i) is more easily met when $\frac{\partial \rho_L}{\partial g_{\neg L}}$ is large and $|\frac{\partial^2 \rho_L}{\partial g_{\neg L}^2}|$ is small, that is, if enforcement is sufficiently effective in the legal market. Thus, when (i) is met, $\frac{\partial F}{\partial g_{\neg L}} > 0$ which, with $-\frac{\partial F}{\partial \bar{\rho}_L} < 0$, implies $\frac{\partial g_{\neg L}}{\partial \bar{\rho}_L} < 0$. Since $g_{\neg L} = T + R - g_L$, then $\frac{\partial g_L}{\partial \bar{\rho}_L} > 0$. $\square$

This reallocation of revenues away from enforcement spending towards public spending unambiguously increases benefit $V_j(\cdot)$ of each illegal producer since $\frac{\partial V_j(\cdot)}{\partial g_{\neg Lj}} < 0$. Lower enforcement spending also decreases the benefit of legal producers, but this is offset by higher public spending. Thus, the net effect on legal producers depends on the marginal benefit of public spending relative to that from enforcement spending. For $\frac{\partial V_i(\cdot)}{\partial g_L} \approx \frac{\partial V_i(\cdot)}{\partial g_{\neg L}}$, then the net effect of on legal producers of an increase in $\bar{\rho}_L$ is close to zero. To the extent that $\sum_i V_i(\cdot)$ and $\sum_j V_j(\cdot)$ capture the size of the legal and illegal markets, then:

Proposition 4. *Provided that enforcement is sufficiently effective in the legal market, then an increase in $\bar{\rho}_L$, e.g. from FCPA enforcement, unambiguously increases the size of illegal markets. The net effect on legal markets is ambiguous – when public spending and enforcement spending are equally effective, i.e.* $\frac{\partial V_i(\cdot)}{\partial g_L} = \frac{\partial V_i(\cdot)}{\partial g_{\neg L}}$, *then an increase in $\bar{\rho}_L$ has no effect on legal markets.*

B Normalized Coefficients

Table A1: Normalized Dynamic Effect of Corruption Enforcement for Main Dependent Variables - C&D (2020a) Estimator

				Full Sample					
	GDP	Corruption			GDP Components				Shadow
	per-capita	WB	PRS	C	I	G	E	M	Economy
Year 0	-0.007	-0.014	0.007	-0.013	**-0.043**	-0.001	**-0.043**	**-0.037**	**0.222**
Year 1	-0.006	-0.005	0.019	-0.009	**-0.045**	-0.002	**-0.037**	**-0.046**	**0.181**
Year 2	-0.004	-0.007	0.019	-0.014	**-0.028**	0.001	**-0.048**	**-0.05**	0.143
				High–Corruption Sample					
	GDP	Corruption			GDP Components				Shadow
	per-capita	WB	PRS	C	I	G	E	I	Economy
Year 0	-0.007	-0.009	-0.023	-0.016	**-0.050**	0.005	**-0.051**	**-0.047**	**0.277**
Year 1	-0.004	0.010	0.004	-0.012	**-0.056**	0.002	-0.038	**-0.054**	**0.226**
Year 2	-0.002	0.013	-0.006	-0.019	-0.033	0.007	**-0.056**	**-0.060**	0.116
				Low–Corruption Sample					
	GDP	Corruption			GDP Components				Shadow
	per-capita	WB	PRS	C	I	G	E	I	Economy
Year 0	**-0.019**	-0.021	**0.055**	-0.014	**-0.036**	-0.025	**-0.036**	-0.023	**0.181**
Year 1	**-0.027**	-0.035	0.064	-0.009	-0.031	-0.026	**-0.045**	**-0.038**	0.173
Year 2	**-0.028**	**-0.050**	0.084	-0.013	-0.018	-0.030	-0.038	**-0.037**	**0.276**

Notes: Bold estimates are statistically significant at the 95% level.

Table A2: Normalized Dynamic Effect of Corruption Enforcement for Other Illicit Variables - C&D (2020a) Estimator

High–Corruption Sample–50th percentile or below				
	Shadow Economy	Homicide Rates	Tree Loss	Trade Misinvoicing
Year 0	**0.277**	0.009	**0.027**	-0.145
Year 1	**0.226**	0.011	**0.019**	0.022
Year 2	0.116	0.001	**0.020**	0.540
Low–Corruption Sample–Greater than 50th percentile				
	Shadow Economy	Homicide Rates	Tree Loss	Trade Misinvoicing
Year 0	**0.181**	-0.008	0.024	-0.993
Year 1	0.173	-0.012	0.007	-0.657
Year 2	**0.276**	-0.010	0.003	0.157

Notes: Bold estimates are statistically significant at the 95% level.

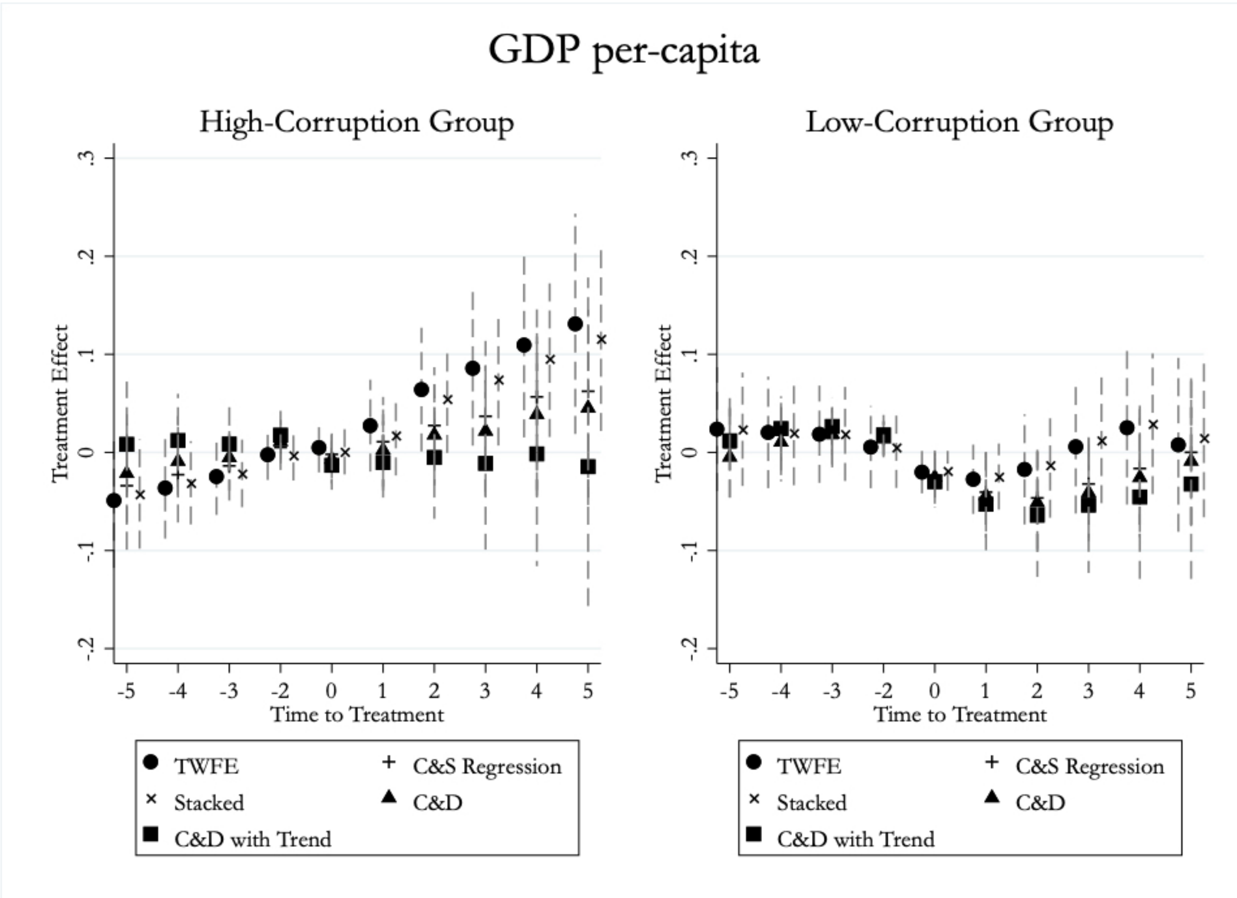
Table A3: Normalized Dynamic Effect of Corruption Enforcement for Other Illicit Variables and Shadow Splits - C&D (2020a) Estimator

Large–Shadow Sample–50th percentile or above				
	Shadow Economy	Homicide Rates	Tree Loss	Trade Misinvoicing
Year 0	**0.248**	0.010	**0.027**	0.155
Year 1	**0.251**	0.018	**0.019**	0.217
Year 2	0.070	0.003	**0.020**	0.723
Small–Shadow Sample–Less than 50th percentile				
	Shadow Economy	Homicide Rates	Tree Loss	Trade Misinvoicing
Year 0	**0.149**	-0.008	0.020	-0.385
Year 1	0.050	-0.012	0.015	-0.318
Year 2	0.208	-0.010	0.014	-0.025

Notes: Bold estimates are statistically significant at the 95% level.

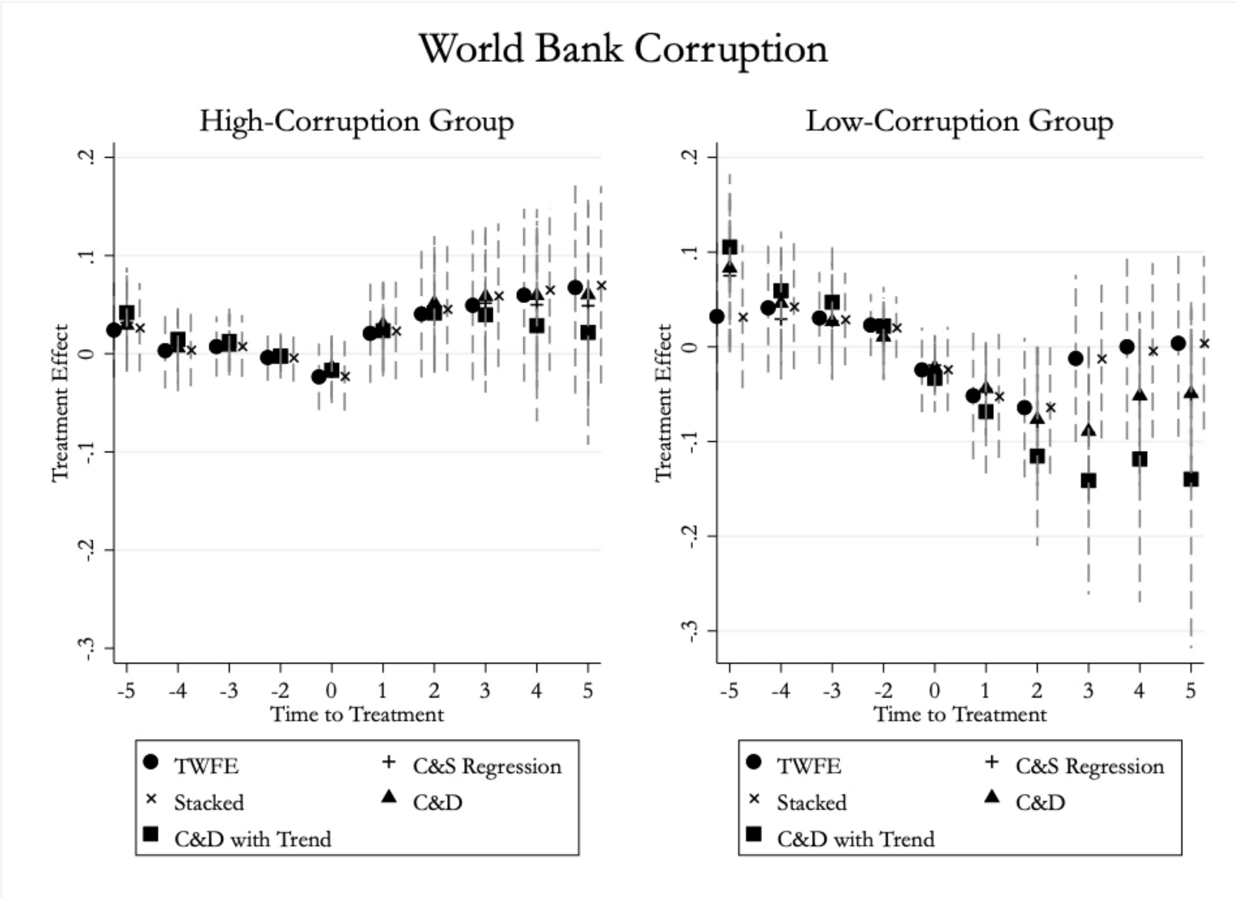
C Split Sample Graphs with Alternative Estimators

Figure B1: Dynamic Effect of FCPA Enforcement on GDP per-capita for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



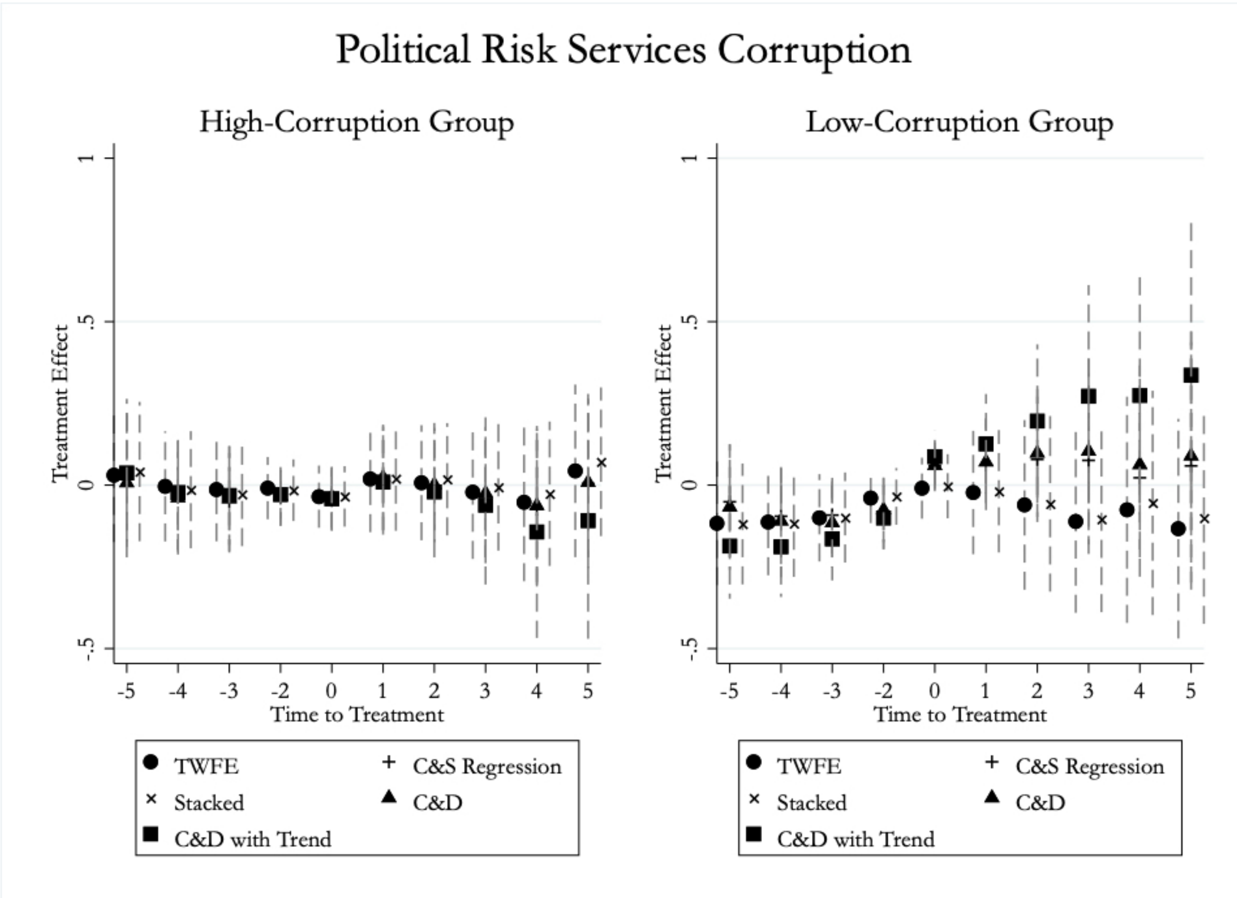
Notes: Bars correspond to 95% confidence intervals.

Figure B2: Dynamic Effect of FCPA Enforcement on World Bank Corruption Perceptions for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



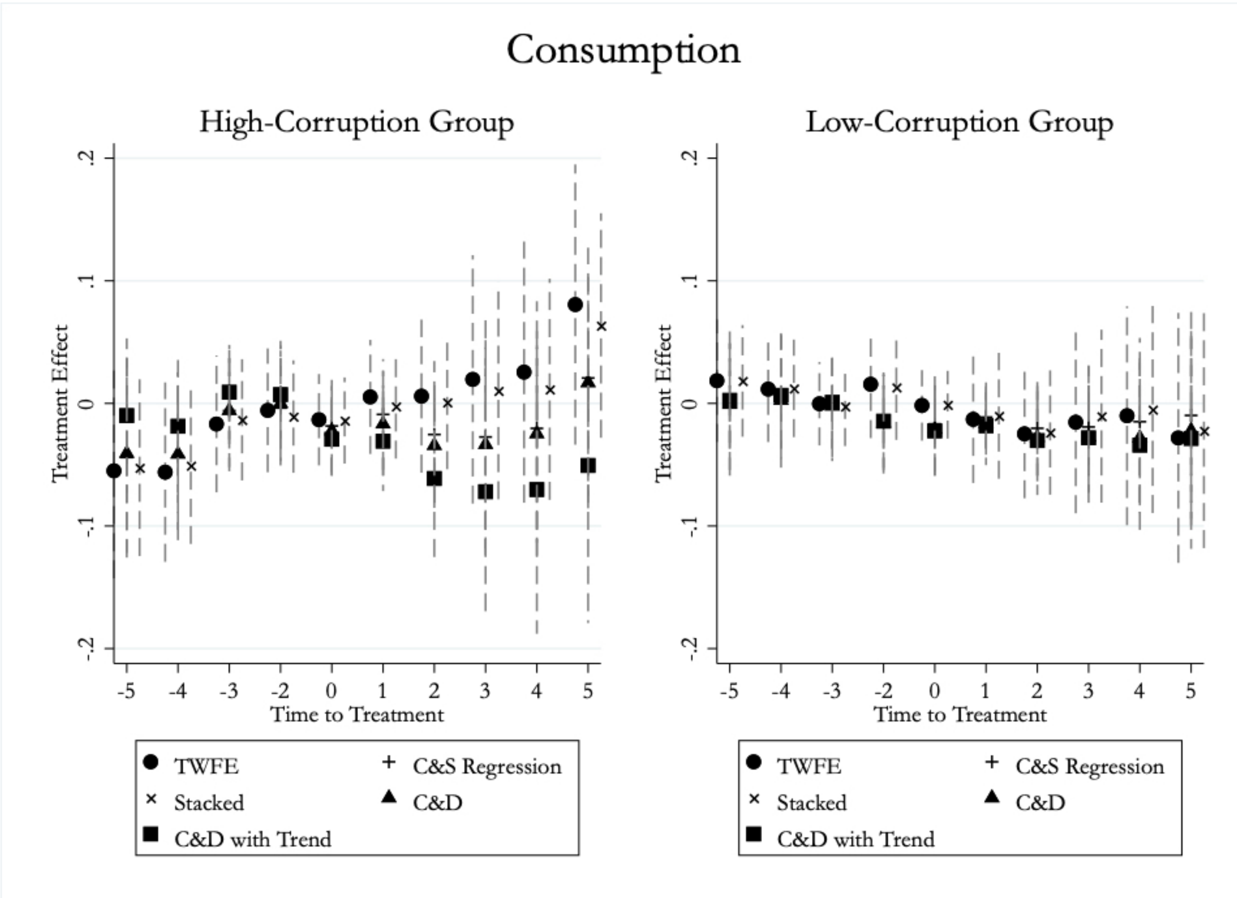
Notes: Bars correspond to 95% confidence intervals.

Figure B3: Dynamic Effect of FCPA Enforcement on Political Risk Services Corruption Perceptions for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



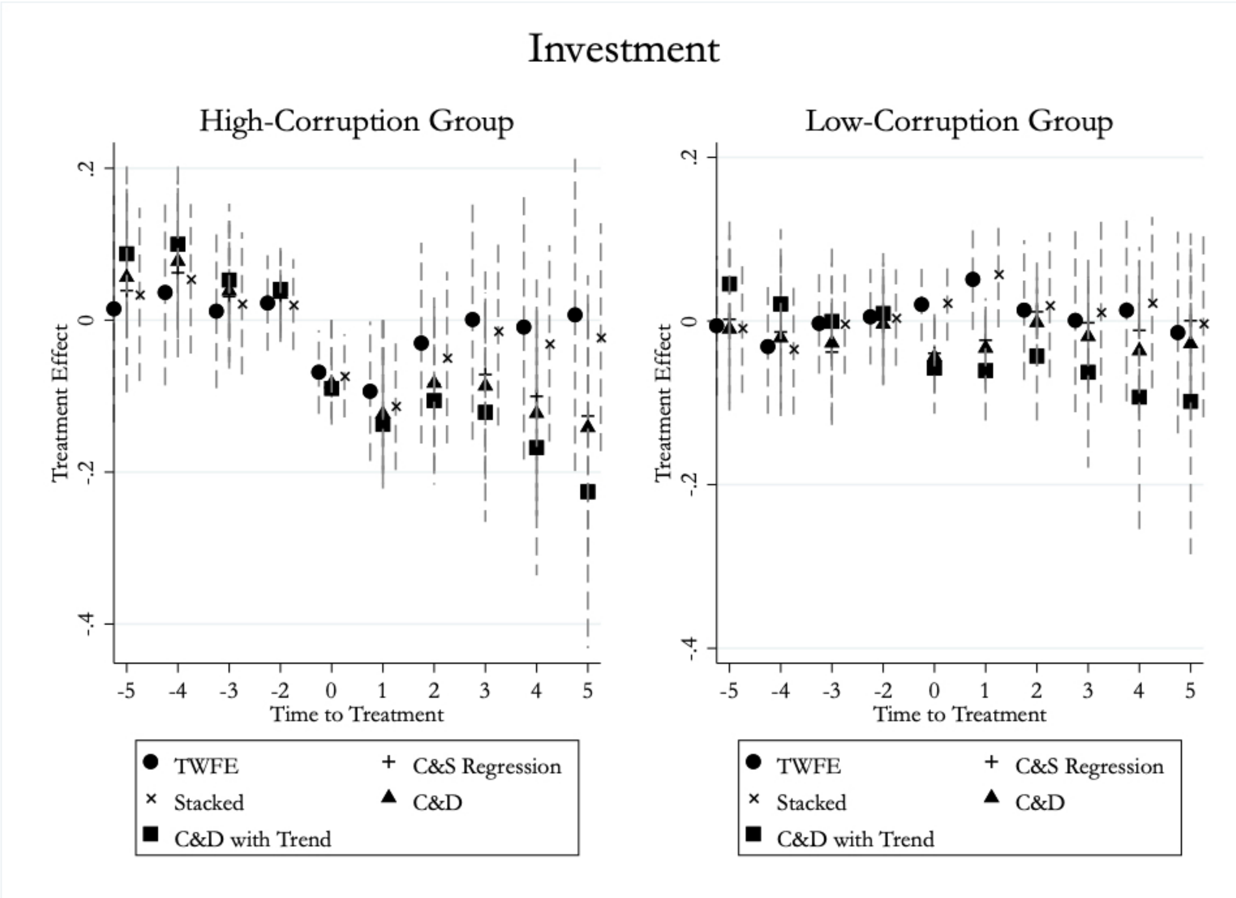
Notes: Bars correspond to 95% confidence intervals.

Figure B4: Dynamic Effect of FCPA Enforcement on Consumption per-capita for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



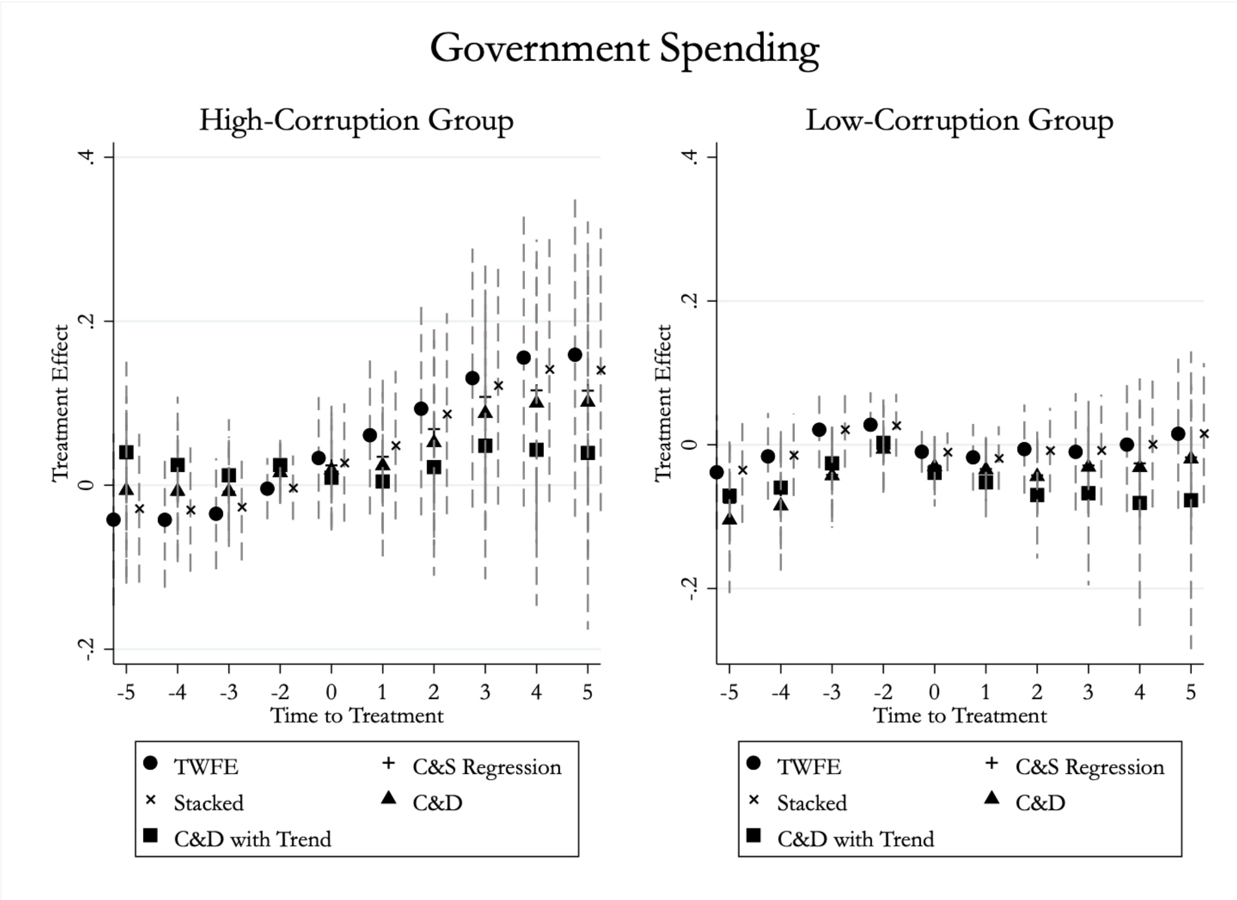
Notes: Bars correspond to 95% confidence intervals.

Figure B5: Dynamic Effect of FCPA Enforcement on Investment per-capita for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



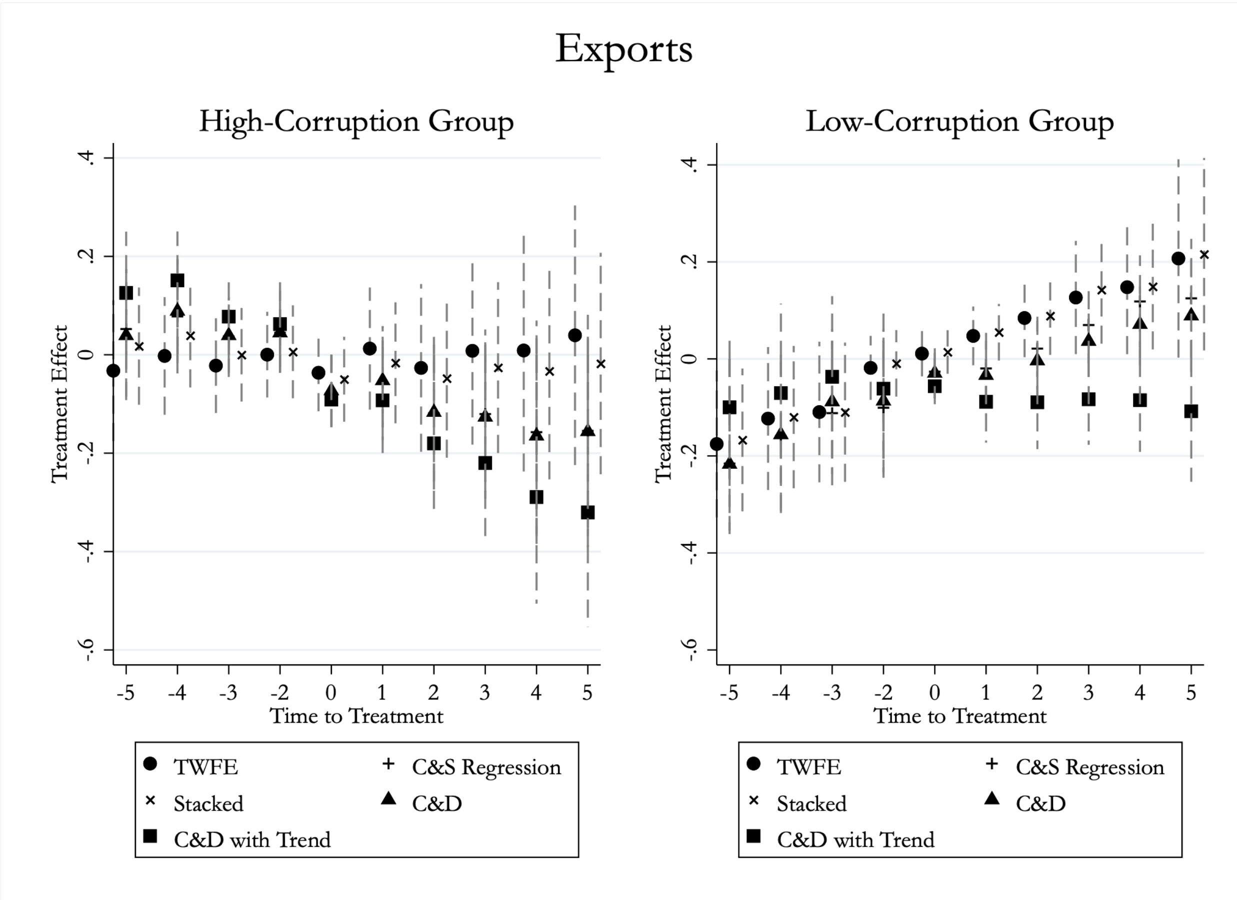
Notes: Bars correspond to 95% confidence intervals.

Figure B6: Dynamic Effect of FCPA Enforcement on Government spending per-capita for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



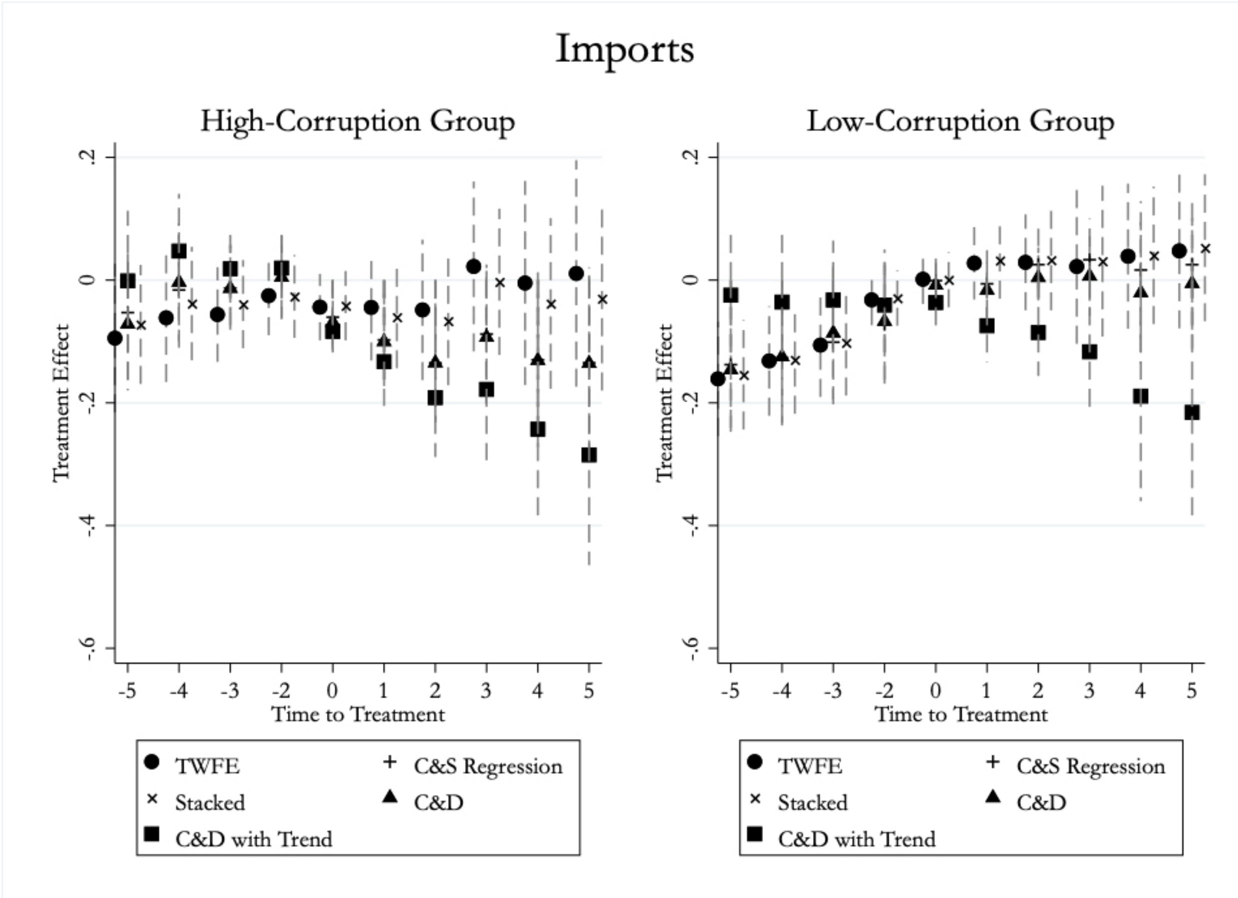
Notes: Bars correspond to 95% confidence intervals.

Figure B7: Dynamic Effect of FCPA Enforcement on Exports per-capita for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



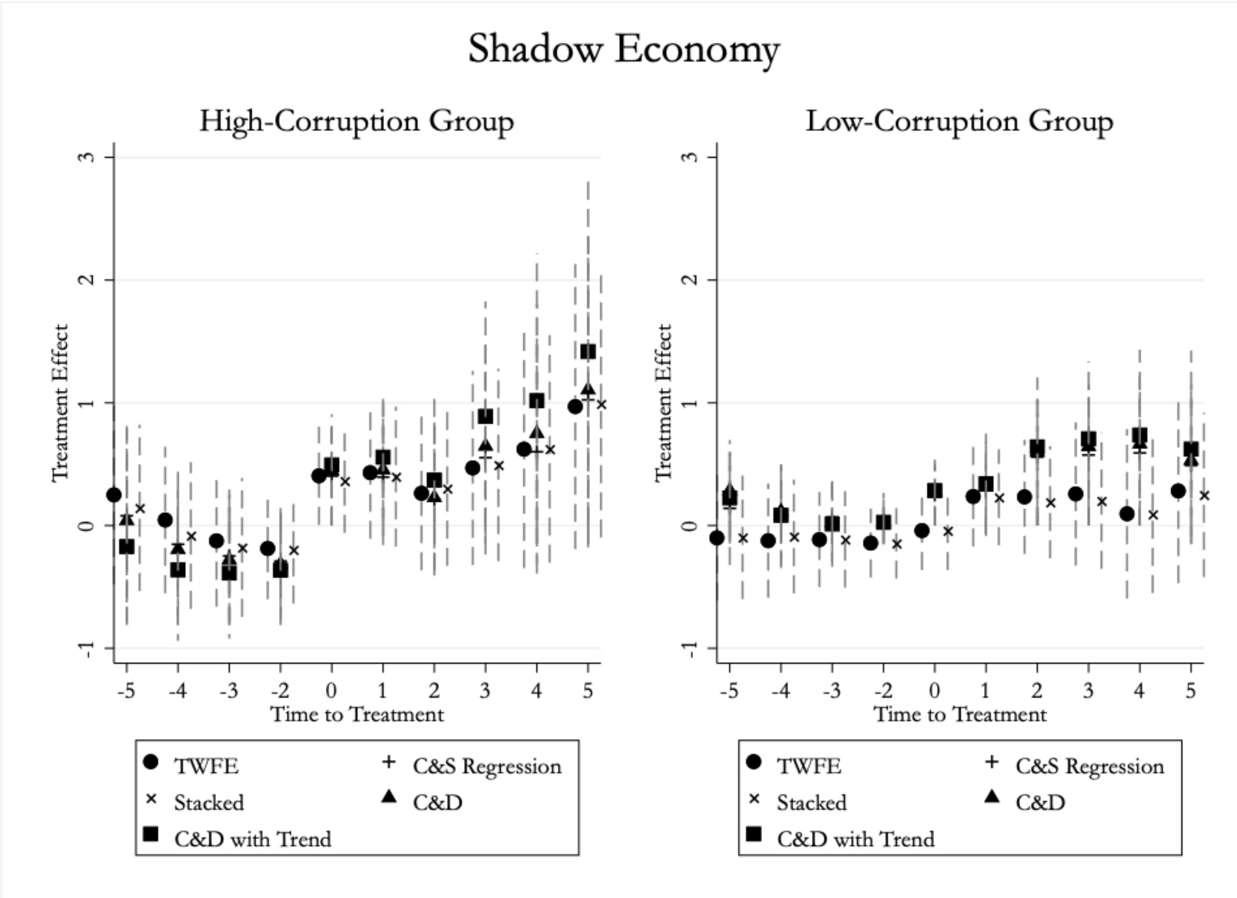
Notes: Bars correspond to 95% confidence intervals.

Figure B8: Dynamic Effect of FCPA Enforcement on Imports per-capita for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



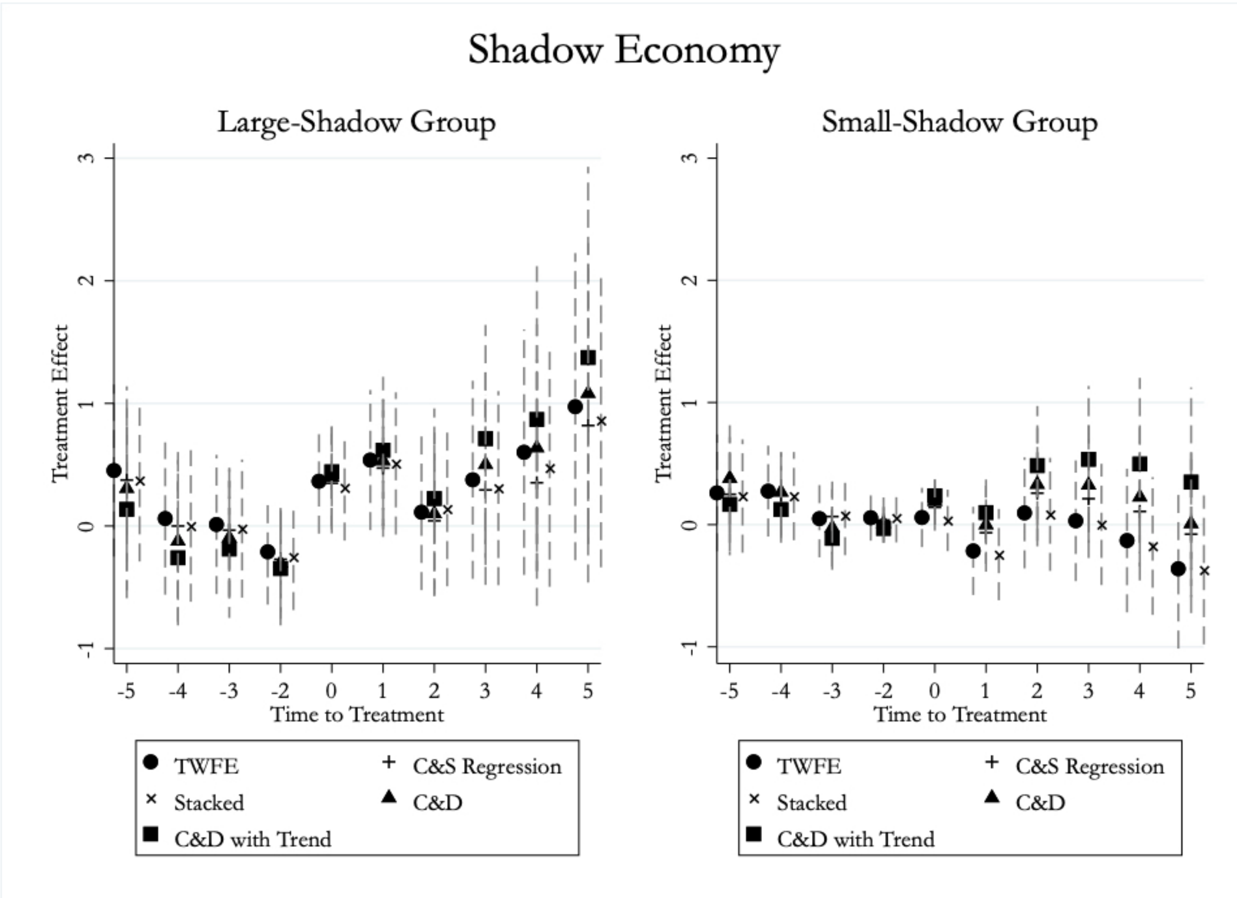
Notes: Bars correspond to 95% confidence intervals.

Figure B9: Dynamic Effect of FCPA Enforcement on the Size of the Shadow Economy for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



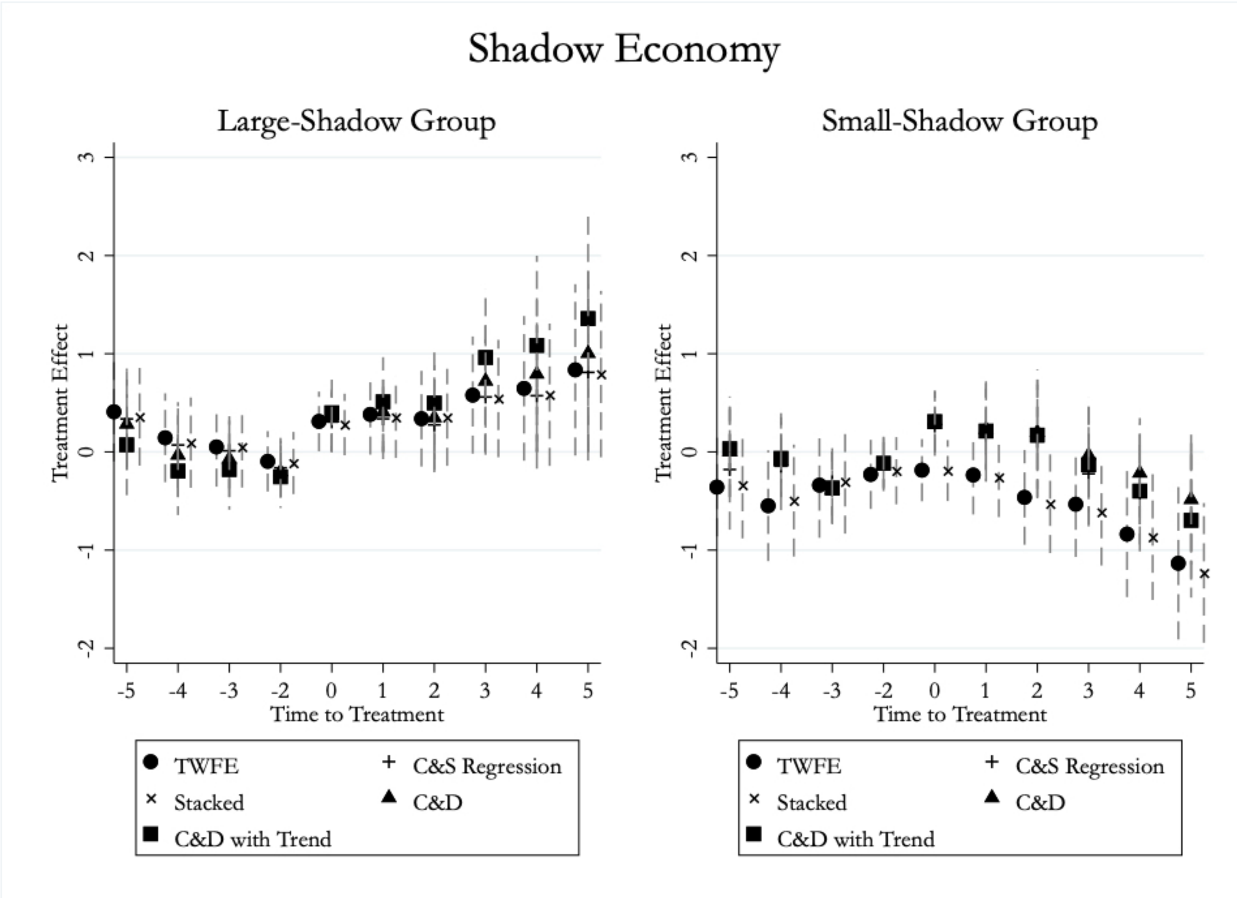
Notes: Bars correspond to 95% confidence intervals.

Figure B10: Dynamic Effect of FCPA Enforcement on the Size of the Shadow Economy for the Large Shadow Group (50th percentile or above) and Small Shadow Group (less than the 50th percentile)



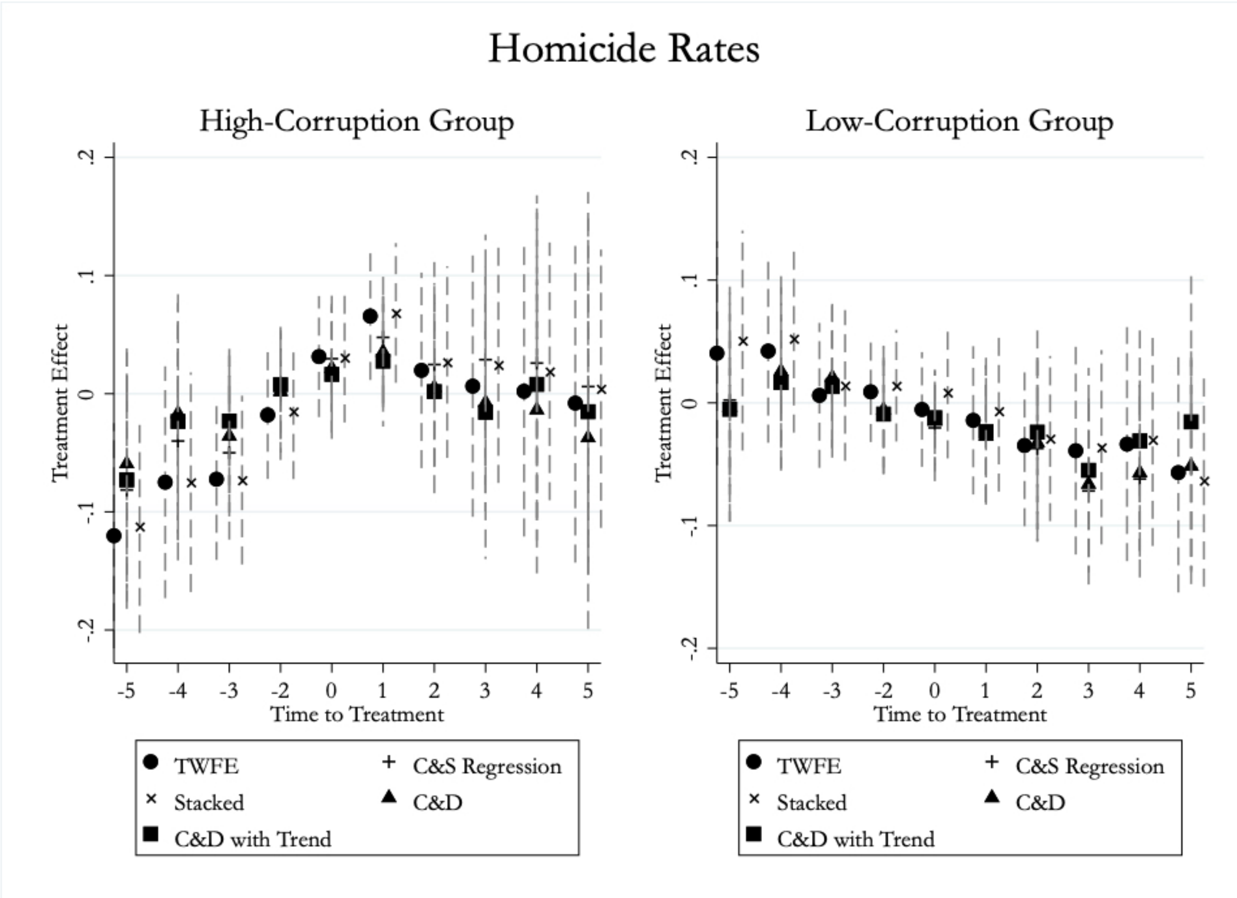
Notes: Bars correspond to 95% confidence intervals.

Figure B11: Dynamic Effect of FCPA Enforcement on the Size of the Shadow Economy for the Large Shadow Group (25th percentile or above) and Small Shadow Group (less than the 25th percentile)



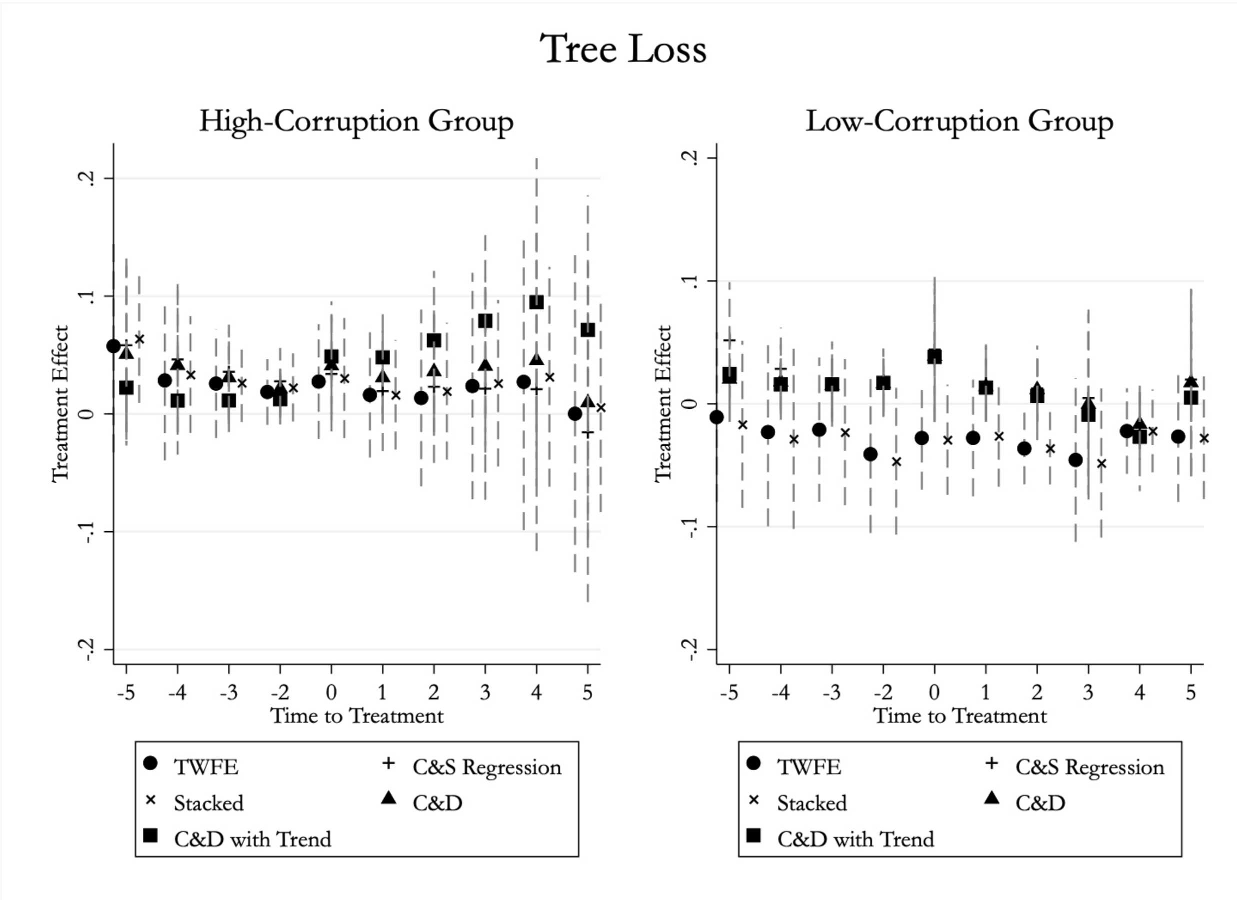
Notes: Bars correspond to 95% confidence intervals.

Figure B12: Dynamic Effect of FCPA Enforcement on Homicide Rates for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



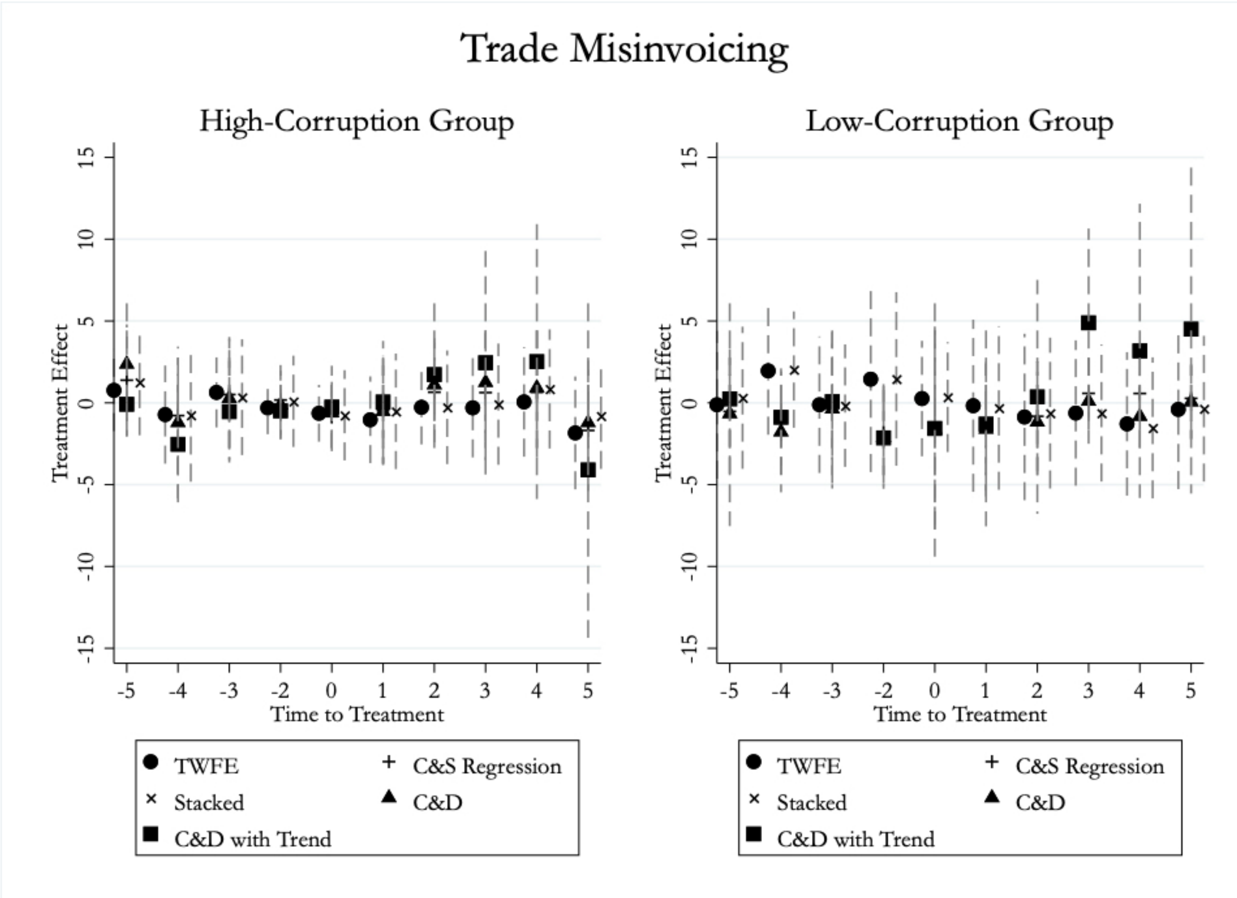
Notes: Bars correspond to 95% confidence intervals.

Figure B13: Dynamic Effect of FCPA Enforcement on Tree Loss for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



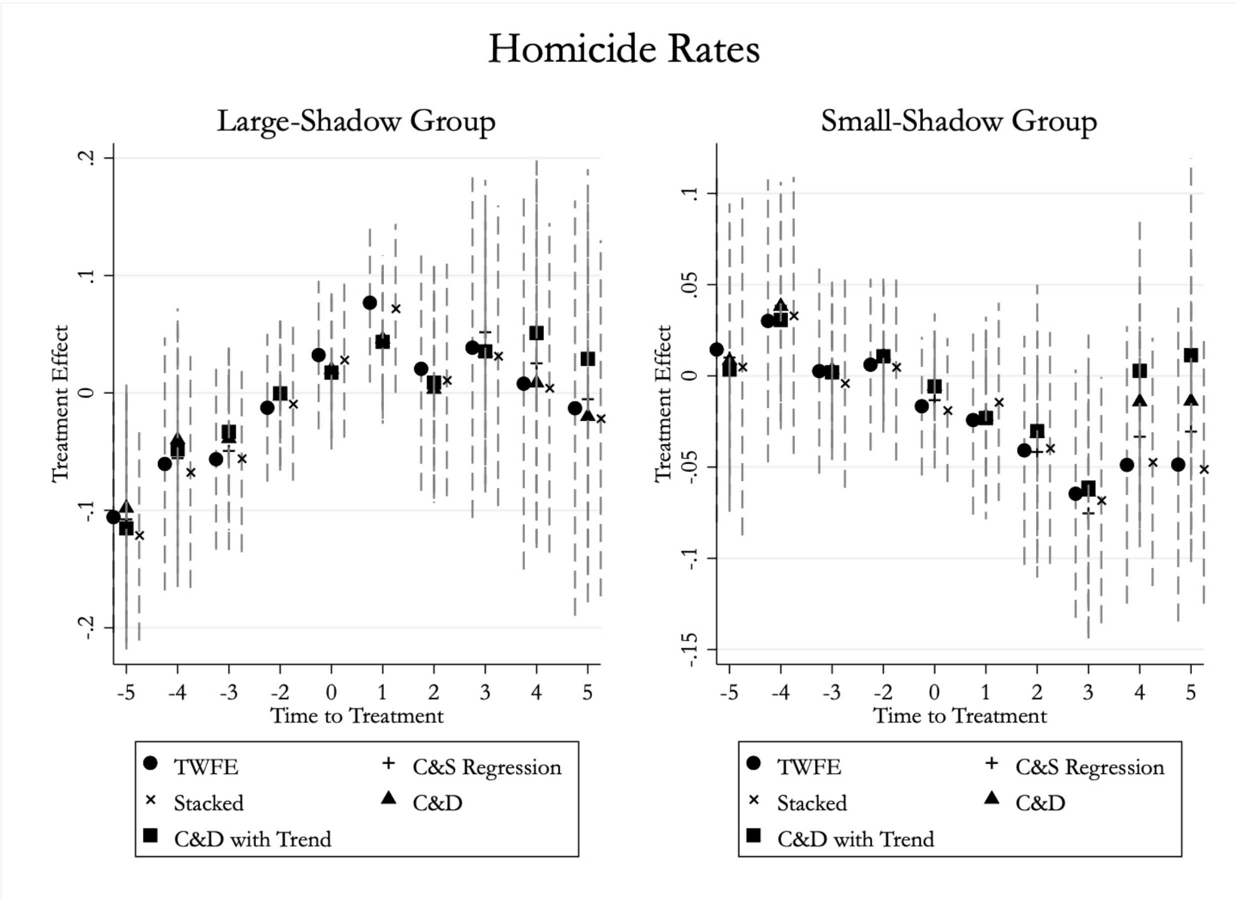
Notes: Bars correspond to 95% confidence intervals.

Figure B14: Dynamic Effect of FCPA Enforcement on Trade Misinvoicing for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



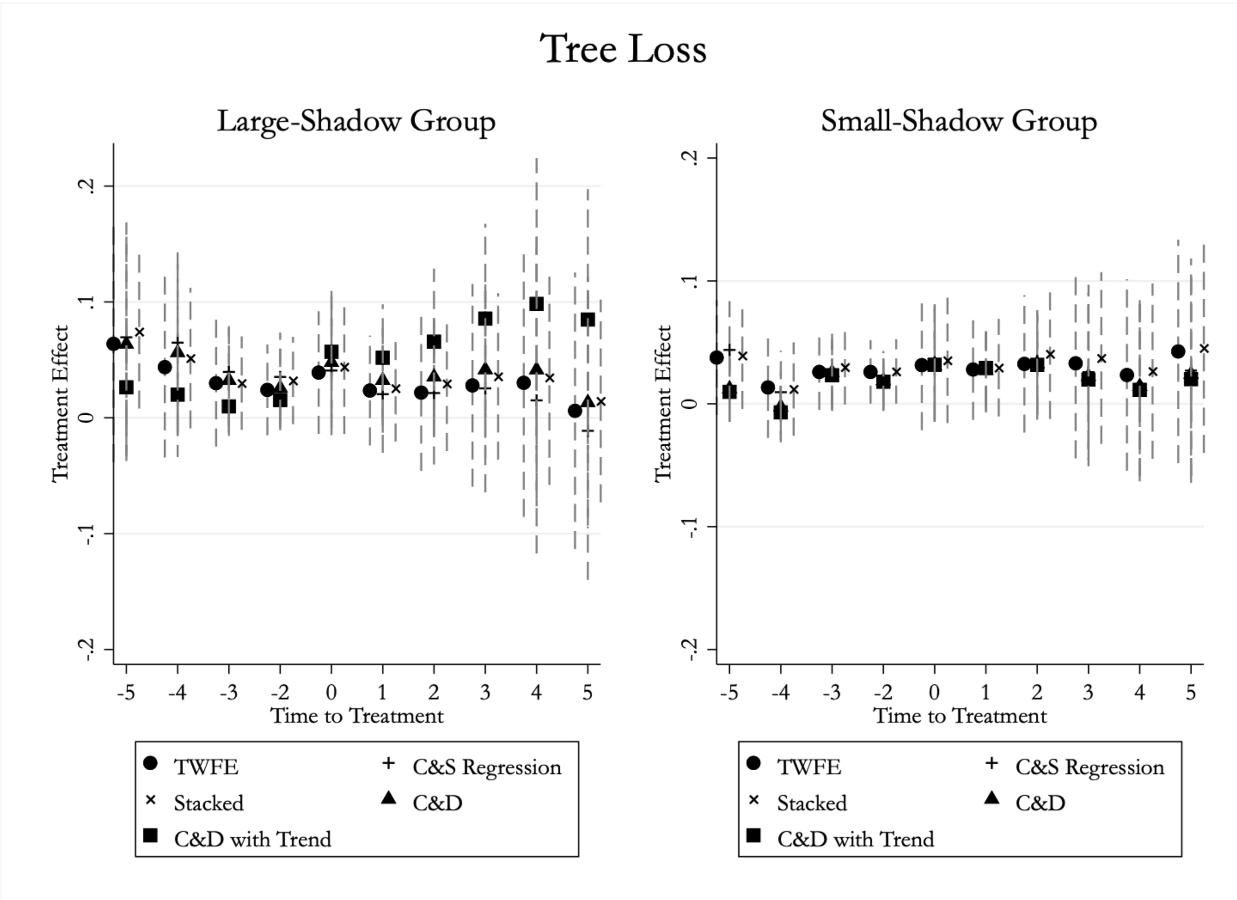
Notes: Bars correspond to 95% confidence intervals.

Figure B15: Dynamic Effect of FCPA Enforcement on Homicide Rates for the Large Shadow Group (50th percentile or above) and Small Shadow Group (less than the 50th percentile)



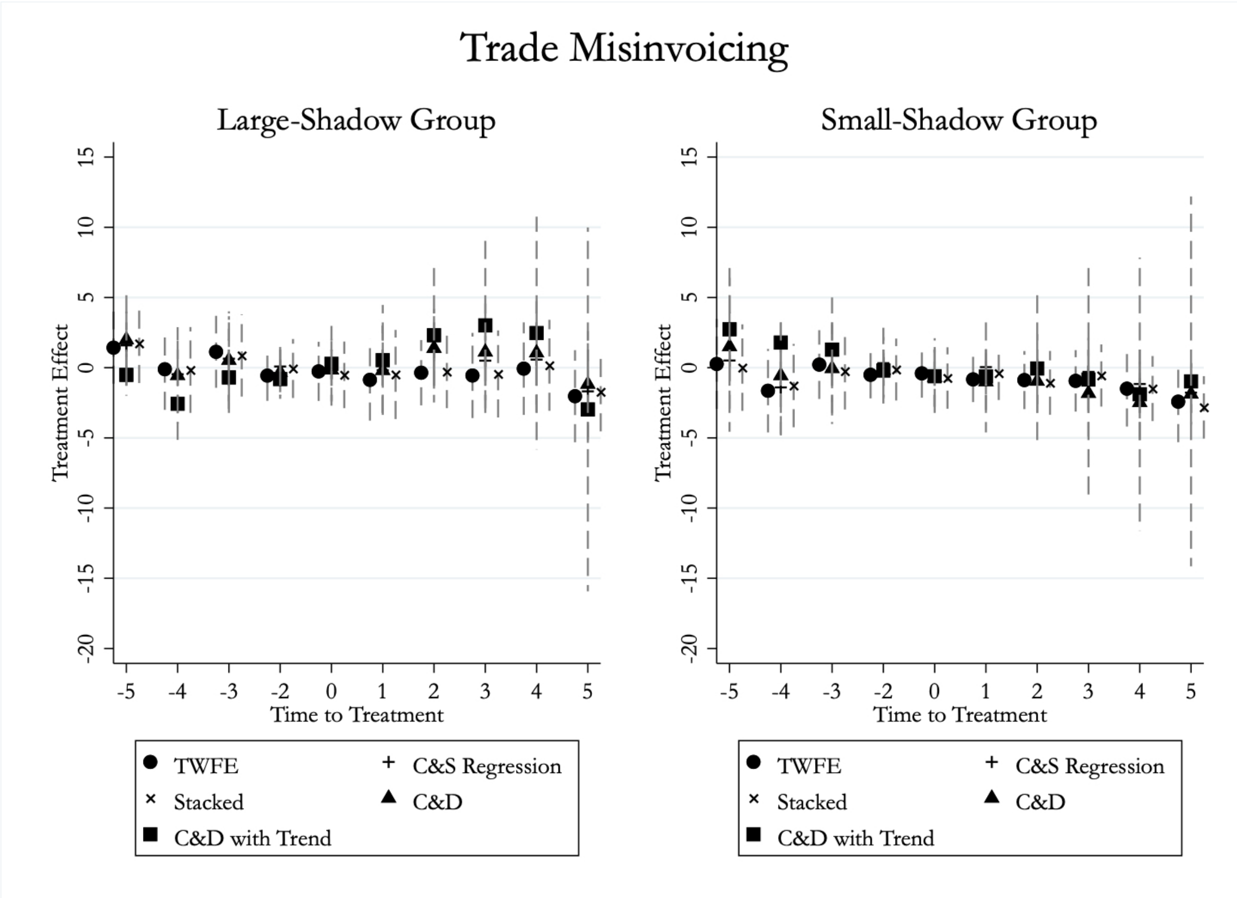
Notes: Bars correspond to 95% confidence intervals.

Figure B16: Dynamic Effect of FCPA Enforcement on Tree Loss for the Large Shadow Group (50th percentile or above) and Small Shadow Group (less than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

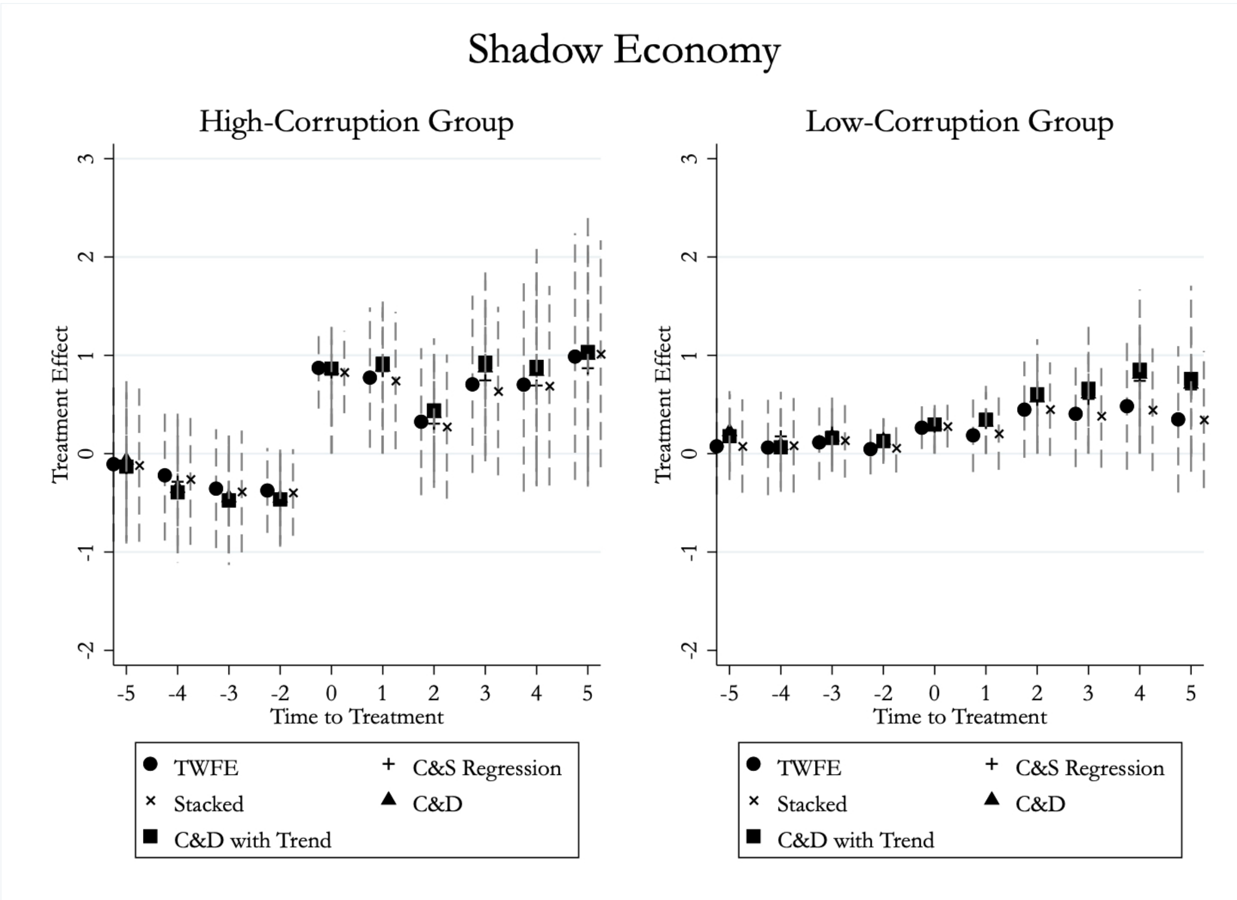
Figure B17: Dynamic Effect of FCPA Enforcement on Trade Misinvoicing for the Large Shadow Group (50th percentile or above) and Small Shadow Group (less than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

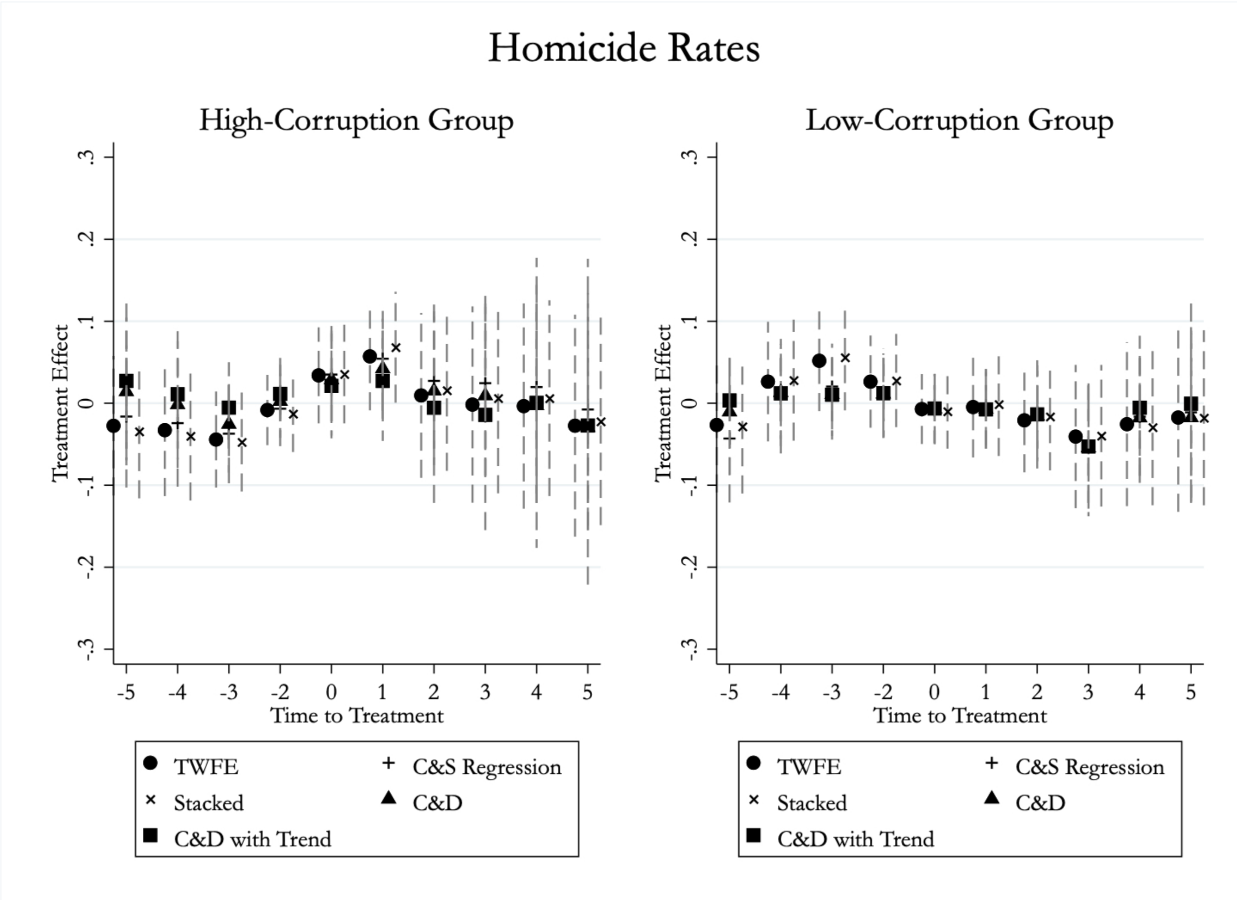
D Illicit Activity - DOJ Only Treatment

Figure C1: Dynamic Effect of FCPA Enforcement on the Size of the Shadow Economy for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



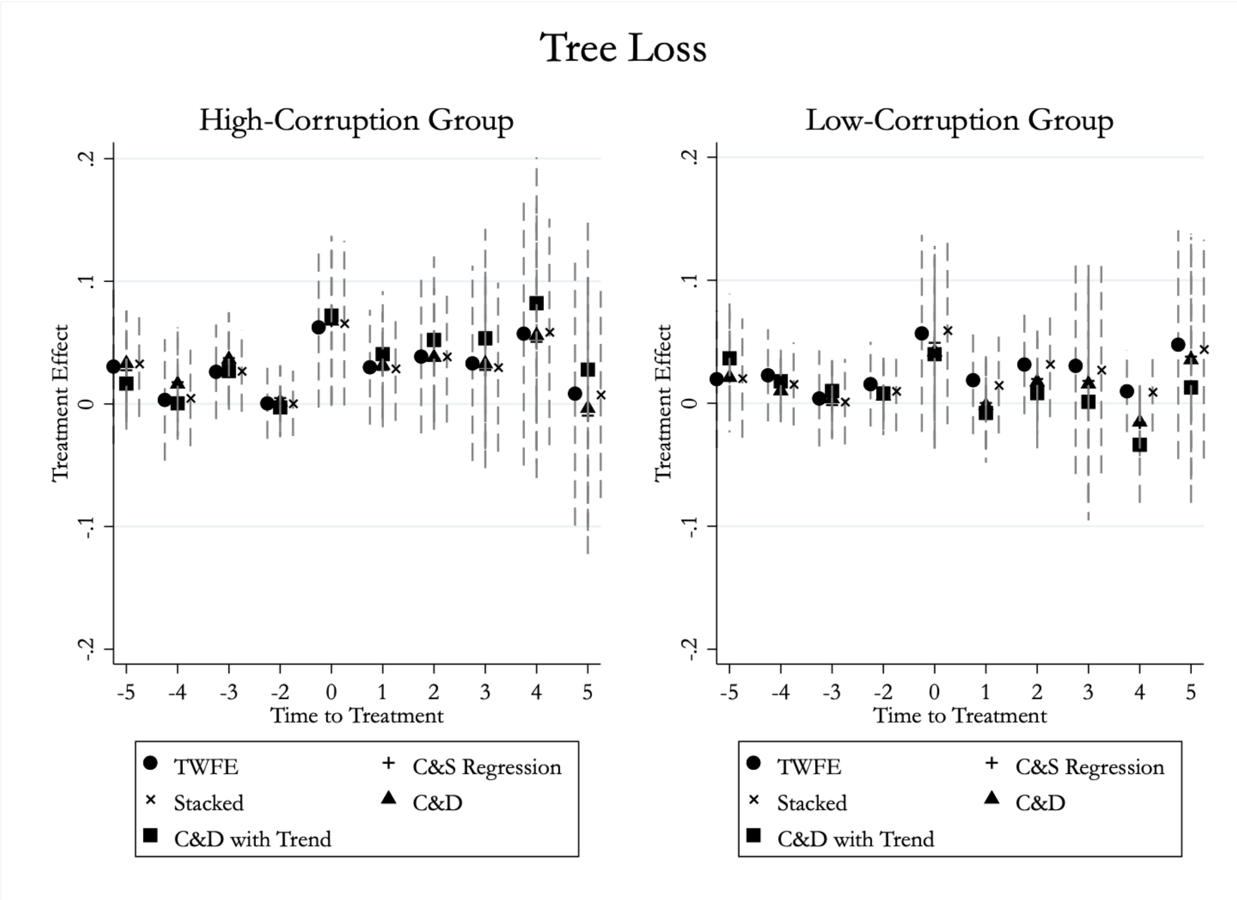
Notes: Bars correspond to 95% confidence intervals.

Figure C2: Dynamic Effect of FCPA Enforcement on Homicide Rates for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



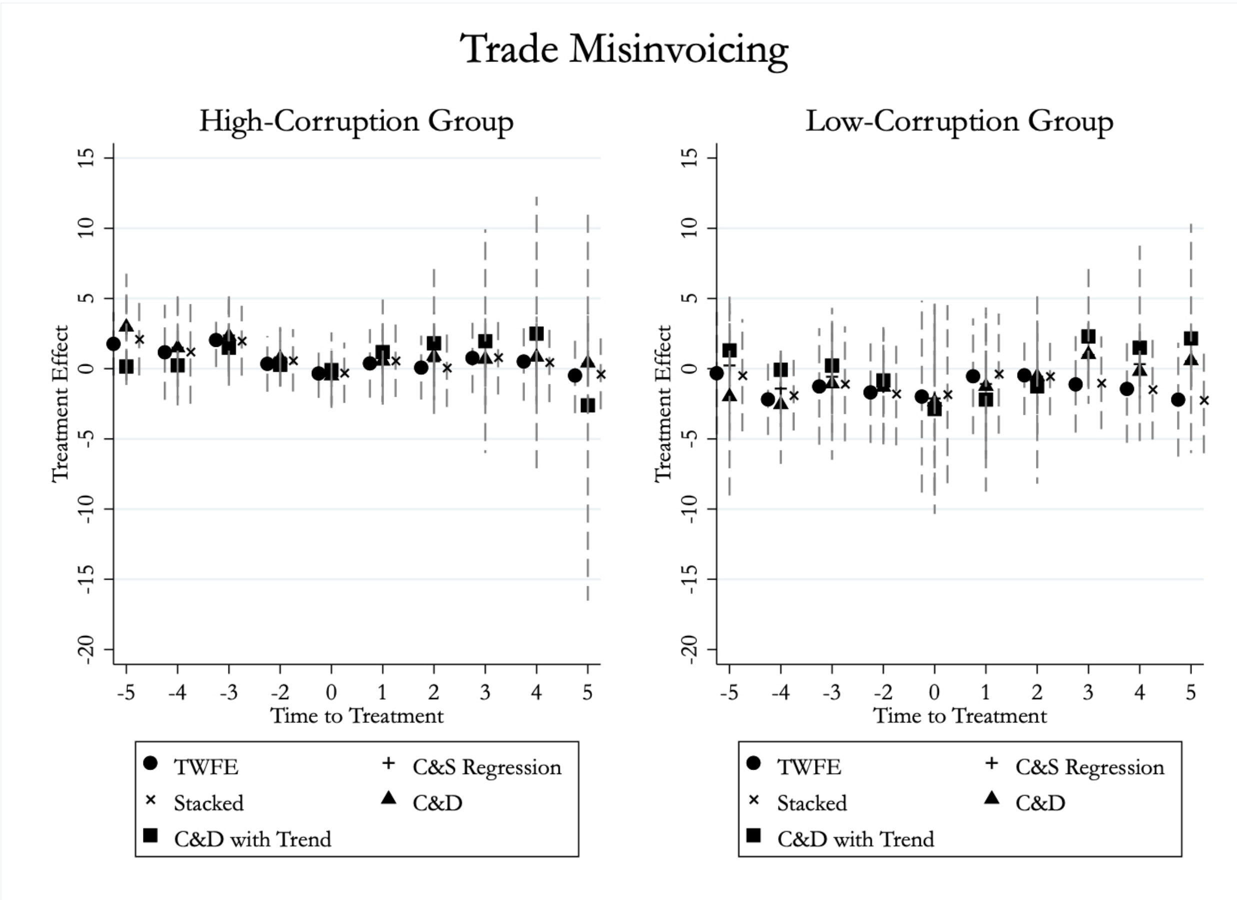
Notes: Bars correspond to 95% confidence intervals.

Figure C3: Dynamic Effect of FCPA Enforcement on Tree Loss for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

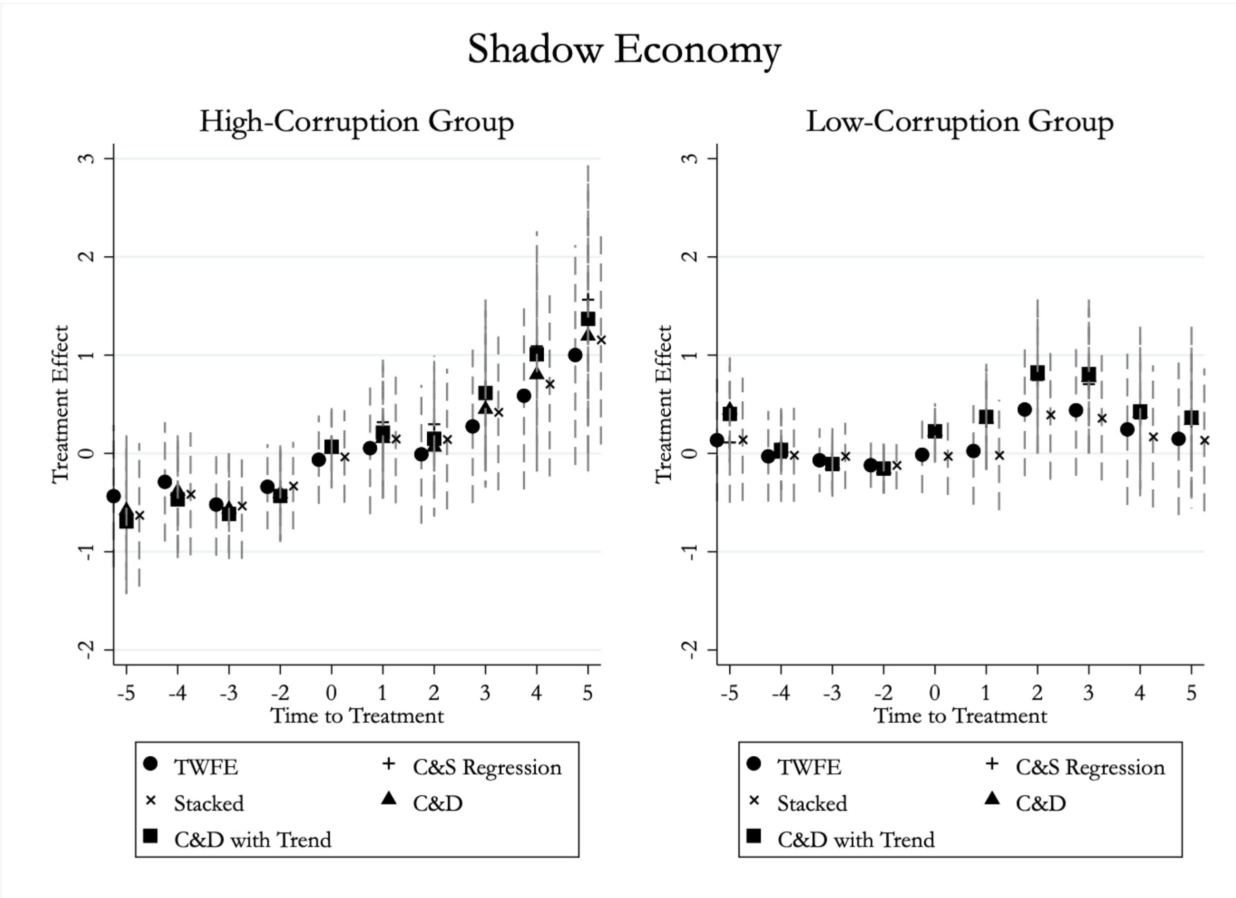
Figure C4: Dynamic Effect of FCPA Enforcement on Trade Misinvoicing for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

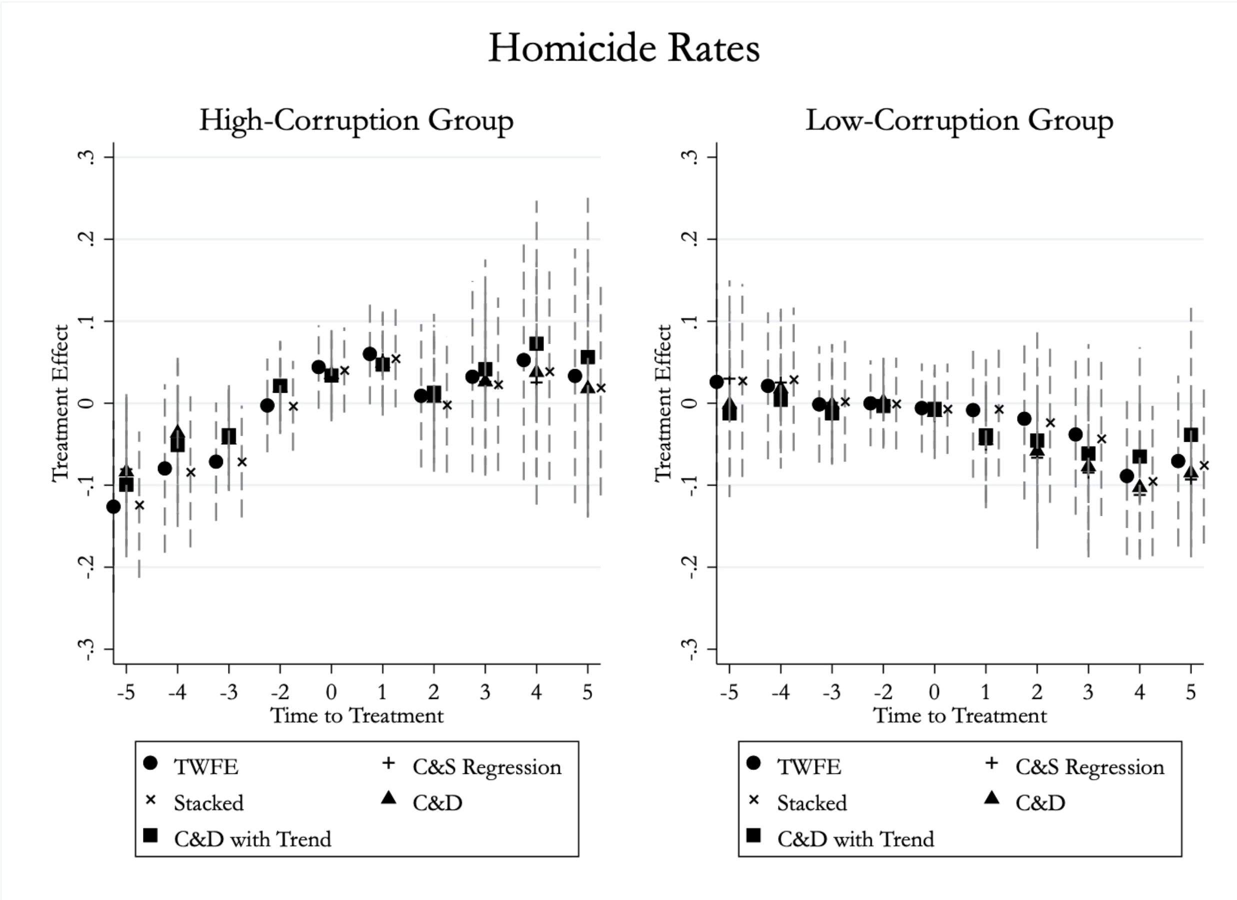
E Illicit Activity - SEC Only Treatment

Figure C1: Dynamic Effect of FCPA Enforcement on the Size of the Shadow Economy for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



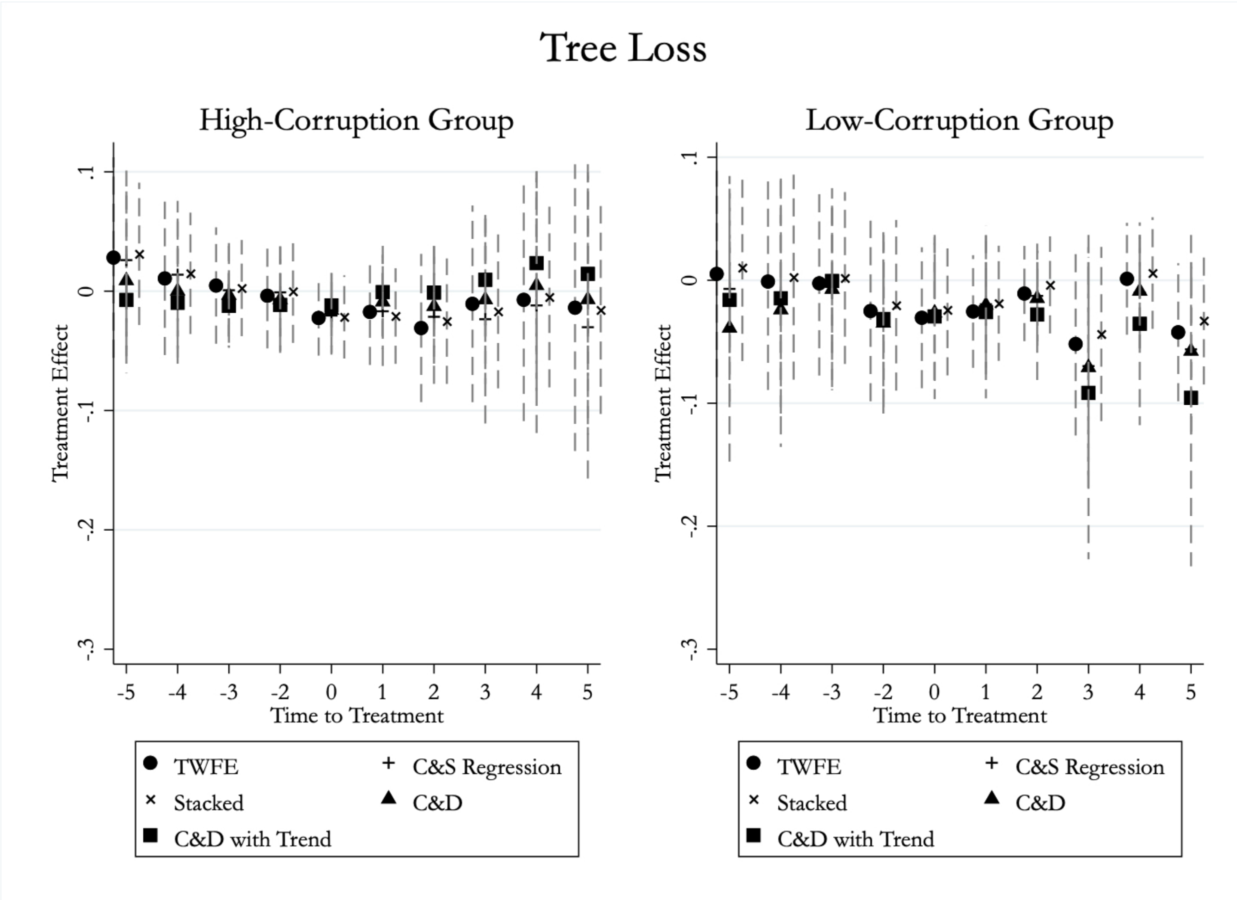
Notes: Bars correspond to 95% confidence intervals.

Figure C2: Dynamic Effect of FCPA Enforcement on Homicide Rates for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



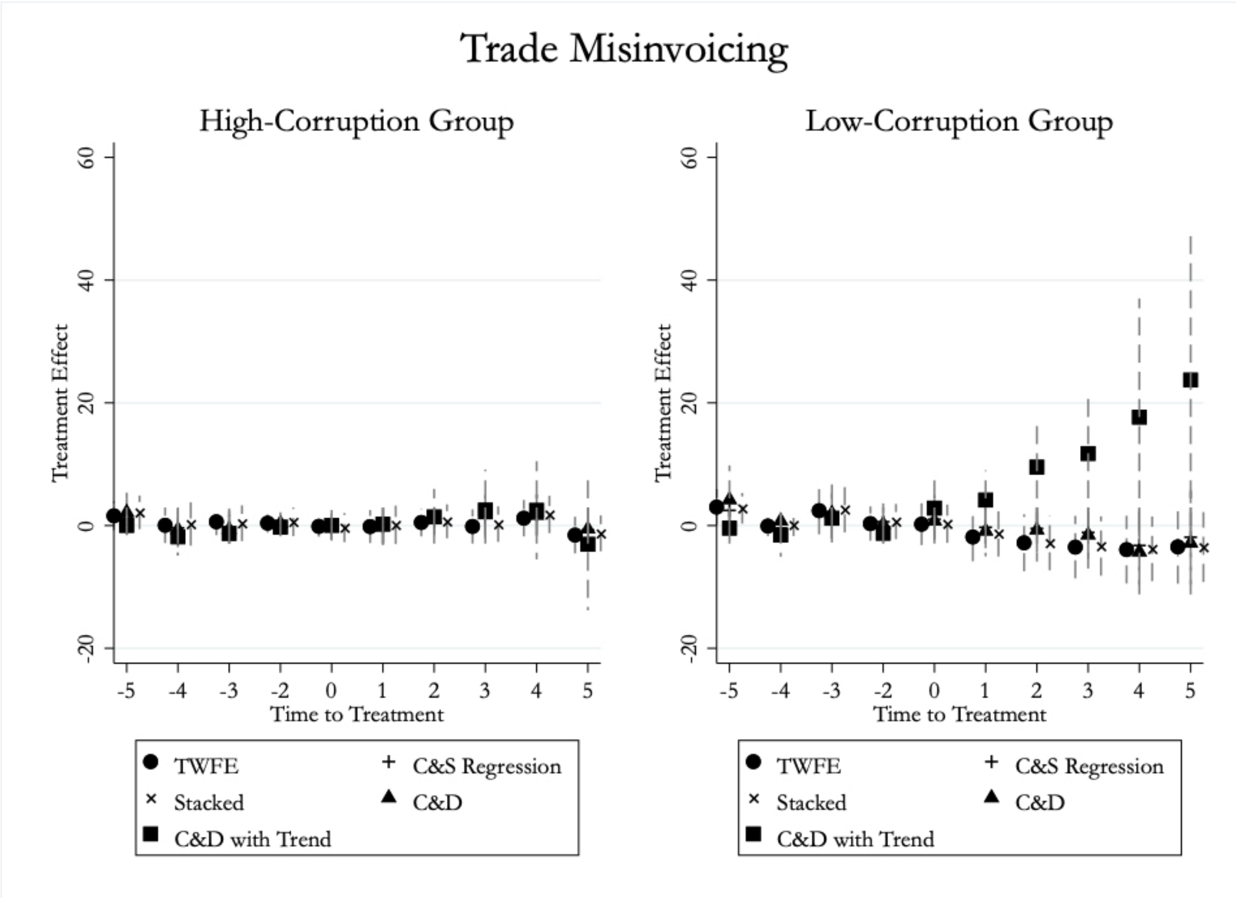
Notes: Bars correspond to 95% confidence intervals.

Figure C3: Dynamic Effect of FCPA Enforcement on Tree Loss for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

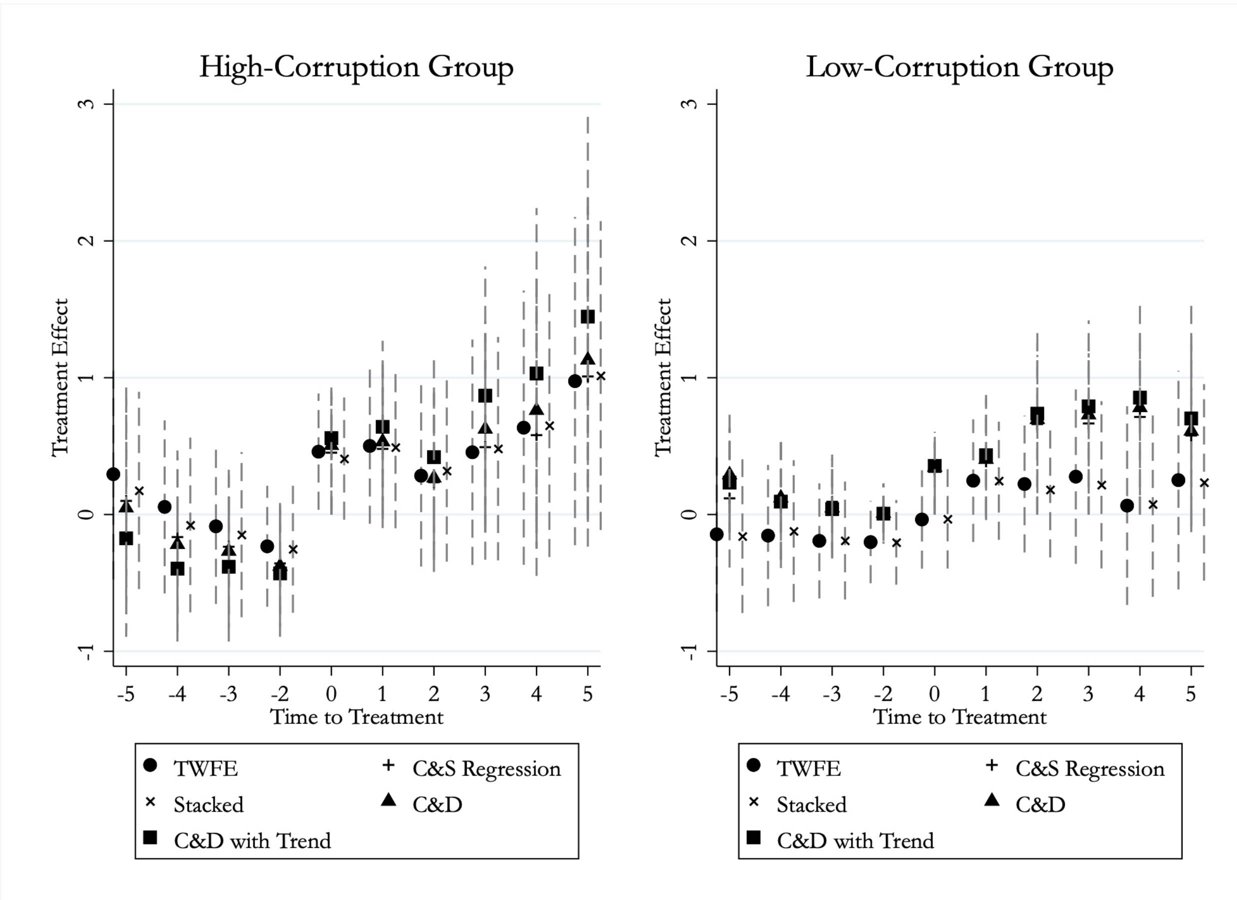
Figure C4: Dynamic Effect of FCPA Enforcement on Trade Misinvoicing for the Corrupt Group (50th percentile or below) and Non-Corrupt Group (greater than the 50th percentile)



Notes: Bars correspond to 95% confidence intervals.

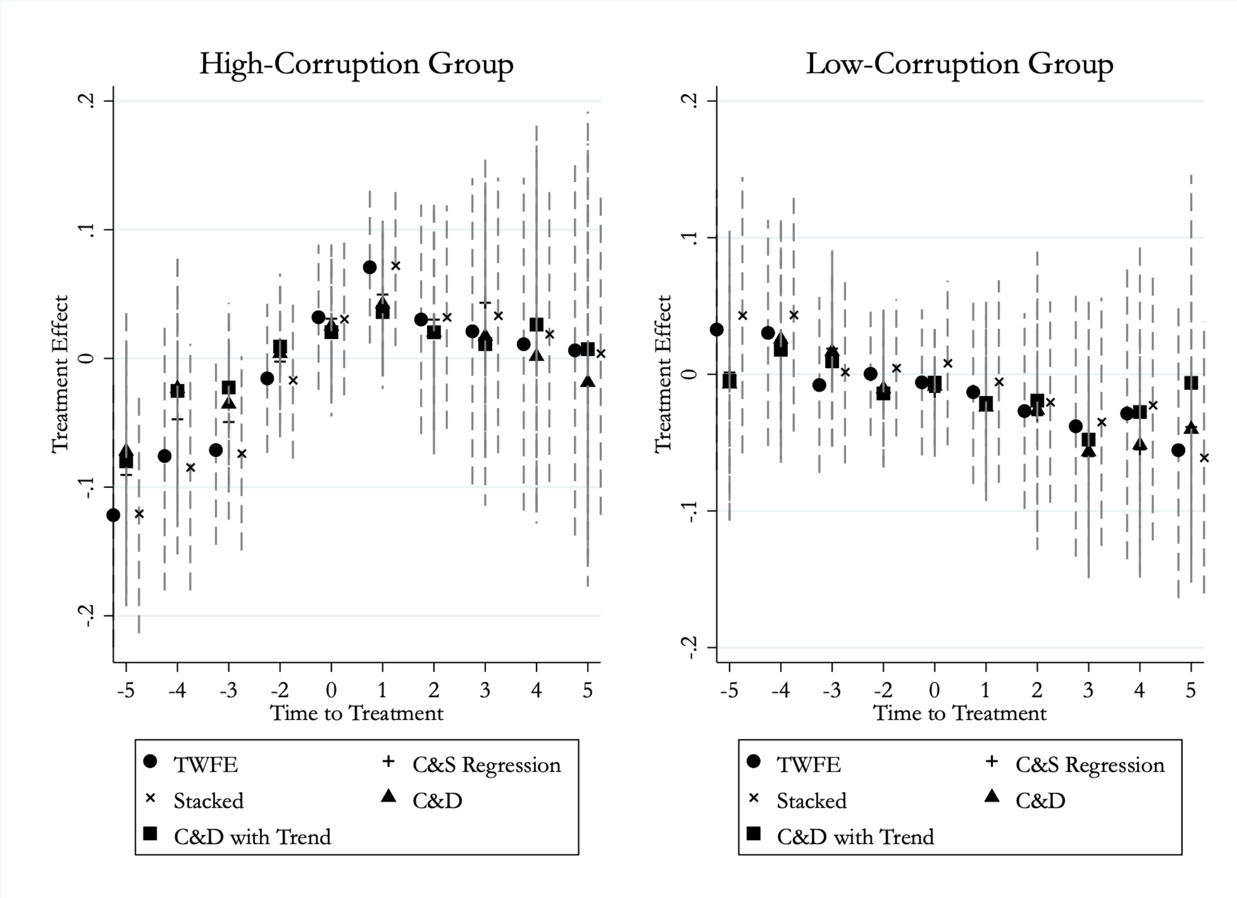
F High– versus Low–Corruption Group Graphs without 1990-1997 Treatments

Figure E1: Dynamic Effect of FCPA Enforcement on the Size of the Shadow Economy



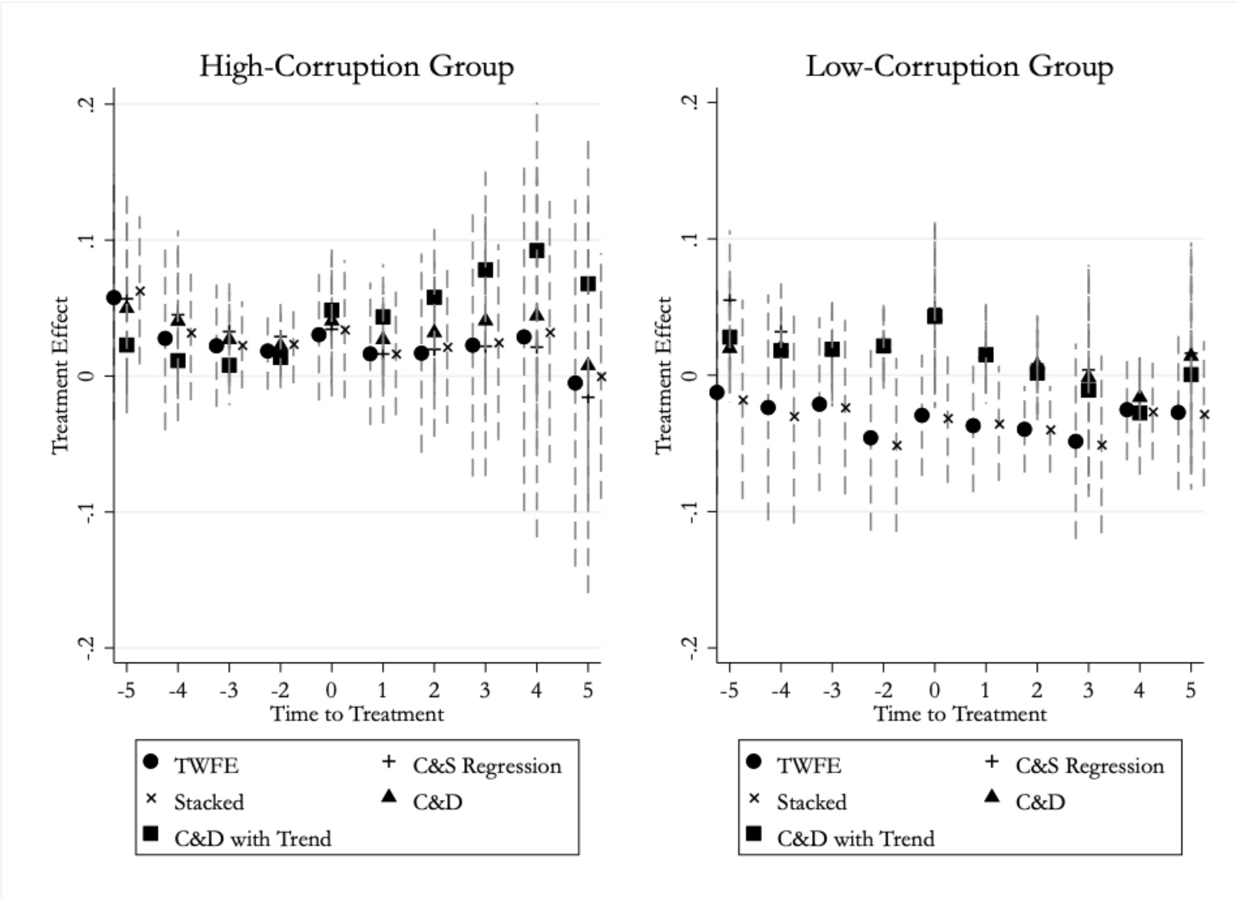
Notes: Bars correspond to 95% confidence intervals.

Figure E2: Dynamic Effect of FCPA Enforcement on Homicide Rates



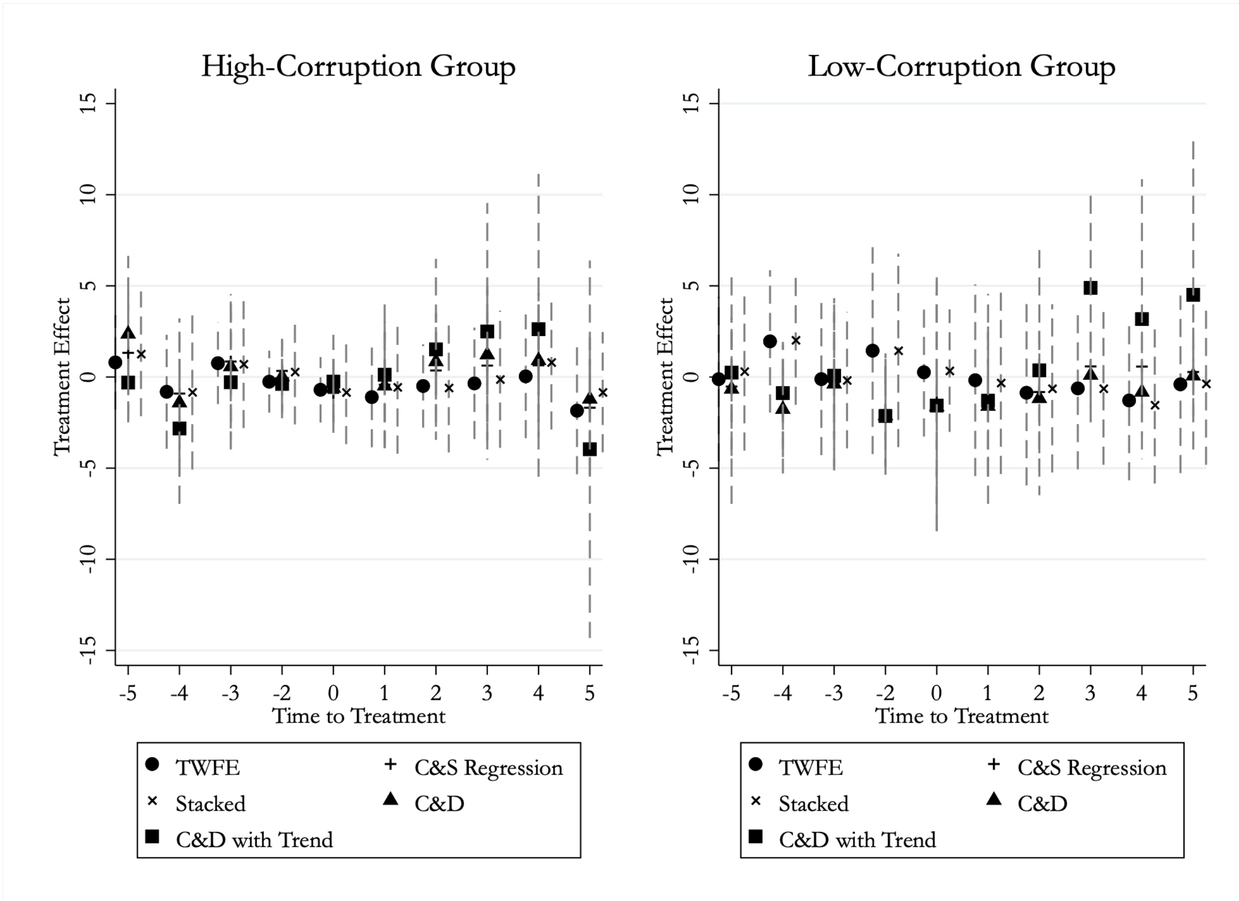
Notes: Bars correspond to 95% confidence intervals.

Figure E3: Dynamic Effect of FCPA Enforcement on Tree Loss



Notes: Bars correspond to 95% confidence intervals.

Figure E4: Dynamic Effect of FCPA Enforcement on Trade Misinvoicing



Notes: Bars correspond to 95% confidence intervals.

G Shadow Economy List

Table G1: Countries Below the 25$^{\text{th}}$ percentile in Shadow Economy Size

Country	Score	Country	Score
Switzerland	7.329	Canada	15.571
Austria	8.814	China Hong Kong SAR	16.214
Luxembourg	10.714	Czech Republic	17.443
Netherlands	11.1	Islamic Rep. Iran	18.371
Japan	11.414	Saudi Arabia	18.471
United Kingdom	11.986	Chile	18.557
New Zealand	12.243	Slovak Republic	18.657
Singapore	12.529	Mongolia	19.186
Germany	12.986	Jordan	19.514
Finland	13.943	Bahrain	19.886
Sweden	13.943	Belgium	20.257
Norway	14.1	Oman	20.329
Australia	14.129	Kuwait	20.371
France	14.514	Syrian Arab Republic	20.386
Iceland	14.614	Vietnam	20.743
Denmark	14.914	Qatar	21.229
Ireland	15.143	Portugal	21.643
China	15.314	Mauritius	23.471