Factors Influencing The Propensity To Bribe And Size Of Bribe Payments: Evidence From Formal Manufacturing Firms In West Africa*

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Abstract

This paper examines the factors which influence who pays a bribe and how much is paid amongst formal manufacturing firms in Nigeria. The study finds strong evidence for the control rights hypothesis: interactions with public officials are positively associated with the incidence of bribery. Evidence is also found for the bargaining hypothesis: that the amount of bribe that a firm pays will depend on its current and future ability to pay as well as its outside options. The investigation contributes to the literature by looking at: different types of interactions with public officials; and the variation in bribery between industry sub-sectors and regions.

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1 Introduction

This paper examines the extent to which government employees are to blame for bribery within Nigeria. This is done by examining the causes of: the propensity to pay a bribe; and the size of the bribe, and also by looking at bribe payments to different types of government employees[1]. Bribery is defined as the giving of informal gifts or payments from businesses to public officials in order to speed up business. This paper uses surveys with data collection strategies that were specially designed to get honest answers from questions concerning bribery. These are used to derive estimates of: the proportion of firms that pay bribes; and the amount of bribes that these companies are required to pay.

This paper uses the control rights and bargaining frameworks, respectively, to examine the nature of corruption in Nigeria. The control rights hypothesis states that the degree of control that public officials have over firms will determine whether or not a firm will be required to pay a bribe. The bargaining framework states that the willingness and ability to pay; and outside options, will determine how much a firm pays, conditional on bribing. This paper contributes to the literature by applying the control rights framework in a West African setting; and by introducing heterogeneous agents: allowing the propensity to bribe to vary depending on different types of public official. By focusing on formal firms, this study is able to look at corruption independently of informality. The manufacturing sector comprises approximately 4% of Gross Domestic Product in Nigeria; and contributed to 7% of G.D.P growth in the last quarter of 2012. Thus, it represents a non-trivial contribution to the overall economy of Nigeria.

The rest of this paper is organised as follows. Sections 2 and 3 discuss the economic literature on bribery and introduce the framework used for this study, respectively. Sections 4 presents the models that are estimated and the methodology that is used, respectively. The data and variables to be included in the model are outlined in Section 5. Sections 6 to 9 present the results and robustness checks. Section 10 concludes and suggests potential avenues for future research.

2 Related Literature

Despite the "efficient grease" hypothesis, which states that corruption can serve to speed up the process of doing business by helping companies to bypass budensome red tape, little empirical evidence has been found for a negative effect of corruption on the coast of capital and bureaucratic delay [Kaufmann & Wei , 1999, De Rosa, Gooroochurn & Görg , 2010]. Moreover, the literature has seen a negative association between bribes paid and firm growth that is sometimes 3 times the size of the detrimental effect of tax on growth [Fisman & Svensson , 2007].

Previous firm level studies on corruption have investigated the drivers of the propensity to pay; and the size of magnitude of bribe, with results indicating that these two things are driven by different processes[Svensson , 2003, Rand & Tarp , 2010]. Further research has compared corruption and informality as potential substitutes/complements. With evidence being found for both relationships to prevail despite the question of the direction of causality [Johnson, Kaufmann, McMillan & Woodruff , 2000, De Rosa, Gooroochurn & Görg , 2010, Rand & Tarp , 2010].

Estimates of the level of corruption can vary depending on whether one chooses to measure the absolute frequency of bribe transactions; the frequency of bribe transactions as a share of the total number of transactions; or the aggregate amount of money paid in bribes [Méndez & Sepúlveda , 2010]. The current study uses a currency measure denoting the actual bribe amounts paid. This allows for an analysis of the factors contributing to the propensity to bribe; and the

[1] "Government employee"; "public official"; and "bureaucrat" are used interchangeably in this paper

factors influencing the bribe amount. Thus, the current investigation uses two out of the three bribe measures stated in Méndez & Sepúlveda [2010], building upon previous work that uses one of the three measures [Delavallade , 2011]. Doing this provides a more comprehensive discussion of the nature of bribery and the factors determining the prevalence; and magnitude of bribe payments amongst manufacturing firms in Nigeria.

Adding bribe amounts to the analysis will also help to decrease potential response bias that can occur when a question is asked that requires the opinion of the interviewee. Two firms, both identical in observable features, might have to pay the same amount of bribe the same number of times per month. Nevertheless, the firms might respond differently to opinion-based bribery related questions. This might act as a barrier to unbiased comparison between firms, however, the use of bribe amounts can help to mitigate this bias.

Unbundling the concept of corruption can help to make progress with finding out facts relating to it (Mishra, 2009)[2]. Different types of corruption can have different effects on an economy and economic agents might settle for some types of corruption as a second best option due to the worse effects of others [Fan, Lin & Treisman , 2010]. A bribe to a customs official might be more expensive than that paid to a traffic police officer. This idea was investigated by Hunt [2006], Hunt & Laszlo [2012] who used data from Peru and Uganda to investigate the supply of bribes in the presence of heterogeneous public officials. The current study adds to this literature by using more types of public officials and therefore adding more heterogeneity to the model.

This paper also adds to the adds to the body of knowledge by unbundling the concept of bribery. The prevalence of and reasons for different types of bribery are laid out. This allows for an understanding of the activities that attract the most graft. Finally, the current paper also builds on previous work by using a much larger sample; and increasing the number of variables used as measures of interactions with government officials.

3 Framework For Modelling The Supply Of Bribes

The control rights hypothesis states that the paying of a bribe is positively related to the amount of contact that a company has with public officials and the regulatory burden that the company faces. The bargaining hypothesis states that the amount of bribe paid is positively related to the current and expected future profits, whilst negatively related to the alternative return on capital stock

This paper uses a simplified version of the model introduced by Svensson [2003], which considers an economy that has a large number of private firms and bureaucrats, with each company being under the jurisdiction of one bureaucrat. Officials act as bribe maximisers, subject to the constraints that: they might get caught and punished; or the firm might exit the market and no longer be able to pay them a bribe.

Public officials who wish to demand bribes will choose to work for government sectors where control rights are relatively high. In a two-sector economy; with a relatively honest sector (s_1) and a relatively corrupt sector (s_2); a randomly picked company is required to pay a bribe with probability:

$$d(i) = \underbrace{\rho(i \in s_2)}_{\text{Probability of being in corrupt sector}} * \underbrace{g}_{\text{Probability that a randomly picked bureaucrat in sector } s_2 \text{ is corrupt}} \tag{3.0.1}$$

Once requested for a bribe, firms can choose to either pay the bribe or exit the industry. Firms will choose to exit if the return from using their capital elsewhere is greater than the

[2] Correspondance with the author

current and future net profits that they would receive if they paid the bribe and stayed in the market.

$$\overbrace{\sum_{n-1}^{\infty}\beta^{n-1}\pi(\kappa k,\cdot|s^{-i})}^{\text{Discounted Profits From Relocating}} \geq \overbrace{\pi(k,\cdot|s^{i})-b_t}^{\text{Current Net Profits}} + \overbrace{E_t\sum_{n-1}^{\infty}\beta[\pi(k,\cdot|s^{i})-d_{t+n}(s^{i})b_{t+n}]}^{\text{Expected Future Profits}} \quad (3.0.2)$$

Where b_t is the amount of bribe paid in time period t; k represents capital stock; κ represents the degree to which capital is sunk; d_t represents the probability that the firm is asked for a bribe at time t; and π represents profit. Firms cannot borrow to pay bribes so in each period net profit must be non-negative:

$$\pi(k,\cdot|s^{i})-b \geq 0 \quad \forall \quad t. \quad (3.0.3)$$

The amount of bribe in equilibrium is determined by:

$$b_t = \pi(k,\cdot|s^{i}) + E_t\sum_{n-1}^{\infty}\beta[\pi(k,\cdot|s^{i})-d_{t+n}(s^{i})b_{t+n}] - \sum_{n-1}^{\infty}\beta^{n-1}\pi(\kappa k,\cdot|s^{-i}) \quad (3.0.4)$$

This has a fixed point, b^*, at:

$$b_i^* = \pi(k,\cdot|s^{i}) + \frac{1-d}{1+\beta d}\beta\bar{\pi}(k,l^{i},\cdot|s^{i}) - \frac{\beta}{1+\beta d}\pi(\kappa k,\cdot|s^{-i})^3 \quad (3.0.5)$$

Therefore the bribe amount is positively related to current and expected future profits, and negatively related to the profit gained from reallocating capital elsewhere ($\pi(\kappa k)$). Higher current or future profits weakens the firms bargaining power, whilst lower sunk costs strengthen its bargaining position.

This framework allows one to model the supply of bribes amongst firms in Nigeria. Whether or not a firm pays a bribe depends on where it chooses to locate. If a firm meets a corrupt public official and pays them a bribe, the amount paid will depend on company specific characteristics. These include: current profits; expected future profits; and the degree of capital mobility.

4 Methodology

Similar to Svensson [2003]; I estimate the probability of a firm paying a bribe:

$$Pr[Bribe] = f(ControlRights_i^{'}\beta) \quad (4.0.6)$$

and the amount of bribe that bribing firms pay:

$$Bribe_i = \beta_0 + \beta_1 profit_i + \beta_2 E[profit_{i;t+1}] + \beta_3 AlternativeReturn_i + \epsilon_i \quad (4.0.7)$$

The previous analysis suggests that $\beta_1, \beta_2 > 0$ and $\beta_3 < 0$

An OLS regression on the bribe amount, using the entire sample, would return biased coefficients due to the censored nature of the data. I consider three alternatives to OLS: the Censored Tobit Model; the Two Part Model; and the Heckman Two-step Procedure.

[3] Where $\bar{\pi}(k,\cdot|s_2) \equiv E_t\pi(k,\cdot|s_2) \quad for \quad all \quad n \geq 1.$

Due to the censored nature of the data on bribes, such analysis can be performed using a censored Tobit model, this would allow for the inclusion of all firms in the bribery equation. This model restricts the sign of the effect of a covariate on the probability of paying a bribe to be the same as the effect of the variable on the amount of bribe paid.

The Censored Tobit Model considered in this study is left-hand censored. The outcome of interest, y, is only observed if the latent variable, y^* exceeds a threshold value. The model assumes additive errors that are normally distributed and homoskedastic. The model estimates both the propensity to bribe and the magnitude of bribe.

$$y^* = \alpha + x^{'}\beta + \epsilon \tag{4.0.8}$$

Where:

$$y = \begin{cases} y^* & \text{if } y^* > 0; \\ - & \text{if } y^* \leq 0. \end{cases}$$

$$\text{And: } \epsilon \sim N[0, \sigma^2]$$

Officials in a heavily regulated industry-location might demand bribes from more firms, however, because of this, the amount of bribe that they require from each company might be less than other industry-locations. The result would be a negative relationship between the propensity to bribe and the size of bribe. In such a case, the coefficient for a dummy that shows whether or not a firm is located in that industry-location would be positive for the selection equation and negative for the outcome equation. In the presence of such a situation the censored Tobit model is misspecified; this restriction can be tested using a likelihod ratio test.

Another potential concern with the analysis is sample selection bias. Equations (3.0.1) and (3.0.5) can be interpreted as a selection model. If the error terms in these two equations are correlated, an OLS regression on equation (3.0.5) will return biased estimates. The selection model can be estimated by a two-step procedure where Equation (3.0.1) is estimated by probit and (3.0.5) with OLS and using an estimate of the inverse Mills ratio from the first step to correct for selection bias. This model can be identified the model by excluding the control rights variables from the second stage of the estimation. The support for this exclusion restriction is based on section 3, that interactions with public officials do not affect the amount of bribe paid.

The Heckman approach allows for the errors from the selection and outcome equations to be interdependent. It does this by including an estimate of the inverse-Mills ratio from the first equation in the outcome equation, thereby treating the selection problem as a problem of omitted variable bias.

$$y_1^* = \alpha_1 + x_1^{'}\beta_1 + \epsilon_1$$
$$y_2^* = \alpha_2 + x_2\beta_2 + \epsilon_2$$

Where:

$$y_1 = \begin{cases} 1 & \text{if } y^* > 0; \\ 0 & \text{if } y^* \leq 0. \end{cases}$$

$$y_2 = \begin{cases} y_2^* & \text{if } y^* > 0; \\ 0 & \text{if } y^* \leq 0. \end{cases}$$

$$\text{With } Cov[\epsilon_1, \epsilon_2] \neq 0$$

In the absence of selection bias, a two-part model can be used to estimate the factors influencing the occurence of bribery and the amount of bribe that is paid. This model is composed of a probit estimation on all firms, and an ordinary least squares regression on those firms that report a positive bribe payment. In the absence of selectivity the two-part model is more robust than the full-information maximum likelihood or two-step Heckman procedure [Puhani , 2000].

Using the two part model to estimate the propensity to bribe and the size of bribe would treat the two processes as independent. The two part model consists of a selection equation (propensity to bribe) and an outcome equation (size of bribe). The selection equation is estimated using the full sample whilst the outcome equation uses the sub-sample of bribing firms, i.e. firms with $y^* > 0$. Since both equations are treated separately the errors are assumed to be independent of each other; and no exclusion restriction is required.

$$y_1^* = \alpha_1 + x_1^{'}\beta_1 + \epsilon_1$$
$$y_2^* = \alpha_2 + x_2^{'}\beta_2 + \epsilon_2$$

Where:

$$y_1 = \begin{cases} 1 & \text{if } y^* > 0; \\ 0 & \text{if } y^* \leq 0. \end{cases}$$

$$y_2 = \begin{cases} y_2^* & \text{if } y^* > 0; \\ 0 & \text{if } y^* \leq 0. \end{cases}$$

$$\text{With } Cov[\epsilon_1, \epsilon_2] = 0$$

In the two-part model the propensity to bribe is estimated as a probit model:

$$Pr[BribeDummy_i = 1] = \Phi(\eta_C' C_i + \alpha_B' B_i) \tag{4.0.9}$$

where $[BribeDummy_i = 1]$ is the case where a firm reports a positive amount of bribe. C_i are the variables in line with the control rights hypothesis. B_i represents the variables in line with the bargaining hypothesis: current profit; expected future profit; and the alternative return on the firms capital stock. Φ represents the standard normal distribution function.

The second part of the two-part model estimates the amount of bribe that is paid using a reduced sample ordinary least squares regression:

$$Bribe_i = \beta_0 + \beta_1 Profit_i + \beta_2 E[Profit_{i,t+1}] + \beta_3 AlternativeReturn_i + \beta_c' \mathbf{C_i} + v_i \tag{4.0.10}$$

where $Profit_i$ denotes the current profit of the firm; $E[Profit_{i,t+1}]$ represents expected future profit; and $AlternativeReturn_i$ is the expected return if the firm reallocates its capital for use in another sector. $\mathbf{C}$ is the vector of variables representing the control rights hypothesis.

In order to decide which model to use I calculate the diagnostic statistics for tests of heteroskedacticity and normality; respectively. I also test to see if the two stages of the model are correlated. In the presence of heteroskedasticity or non-normality, the two-part model performs better than the Censored Tobit model. Neither homoskedasticity or normality is required for consistency in the two-part model. Furthermore, the two-part model is more flexible than the Tobit model since it allows for the covariates to have different signs and magnitudes in the slection and outcome equations, respectively [Clist , 2011]. Furthermore, the two-part model allows for the explanatory variables in the two equations to be entirely different from each other.

If, after controlling for regressors, firms with positive bribes are randomly selected from the population, then the two-part model performs better than the Heckman-Selection model. So

Table 1: Diagnostic Statistics To Choose Between Estimators (Baseline Model)

Estimator	Censored Tobit		Two Part Model		Heckman MLE[4]	Heckman Two-Step
Test	Normality	Homoskedasticity	Normality	Homoskedasticity	$(Cov[\epsilon_1, \epsilon_2] = 0)$	$(Cov[\epsilon_1, \epsilon_2] = 0)$
Test Statistic	52.243	142.430	.	292.31	1.43	-0.98
P-Value	0.0000	0.0000	0.0000	0.0000	0.232	0.326

if there is no strong correlation between the unobservables in the selection equation and the outcome equation, then the Two-Part model will do better.

Table 1 shows diagnostic statistics to choose between the 3 main estimators. These statistics are based on results from the baseline estimation. Results from the augmented estimations do not qualitatively differ from the baseline model. The table shows the results from conditional moment tests of normality and homoskedasticity for the Tobit model; result from skewness/kurtosis and conditional moment tests for normality and homoskedasticity, respectively, in the Two-Part model; and the estimated correlation between the selection and outcome equations.

Results show a strong rejection of normality and homoskedasticity for the Tobit model and the Two-Part model. This suggests that the Two-part model is preferred to the Tobit model for this analysis since it does not require either normality of homoskedasticity for consistency. The test for the correlation between the errors of the selection and outcome equation was computed by running Heckman MLE and Two-Step models with no exclusion restrictions. The results of the tests fail to reject the null of zero correlation between the errors for the selection and the outcome equation. Therefore, the two-part model seems to be the most appropriate choice for the subsequent analysis.

In this study, $profits_t$ are treated as exogenous to bribe $payments_t$. Reasons for this include the fact that firms reported bribe payments to "get things done" with regard to customs, taxes, licenses, regulations, services. The argument proposed is that such informal payments are not a significant determinant of profits compared to, for example, bribes paid for government contracts. Bribes were smaller than all other components of cost. Less than the cost of: Raw materials and intermediate goods; labour; annual depreciation; rental of land/buildings; equipment; furniture; electricity; fuel; water; transportation for goods; communication services; expenditure on capital; expenditure on land and buildings, respectively. Median $Bribes/(operatingcosts + interestpayments) = .04$ for bribing firms; .001 for all firms. However, as a robustness check, an IV-estimation is run. In the IV model profits are instrumented for using: a dummy for foreign ownership; a dummy for university education of owner/majority shareholder; age of the firm; annual expenditure on security (per employee); and sub-sector-location average profit (per employee).

A further issue that is tackled is the potential misclassification of bribe reports. Despite the assurance of anonymity and non-disclosure, some firms might have been unwilling to report a positive bribe. In this case there is potential misclassification in the binary dependent variable for bribery, i.e. there is a positive probability of having a false-negative response to the question on bribery: $\alpha_1 \equiv Pr(y^{observed} = 0|y^{true} = 1) \neq 0$. Where α_1 is the probability of a company falsely denying that it paid a bribe; $y^{observed}$ is the observed response; and y^{true} is the true outcome. The expected value of $y^{observed}$ becomes:

$$E(y_i^{observed}|x_i) = Pr(y_i^{observed} = 1|x_i) = (1 - \alpha_1)F(x_i^{'}\beta) \tag{4.0.11}$$

[4]Heckman MLE & Two Step calculated without exclusion restriction

where $F(\cdot)$ is the cumulative distribution function for the binary outcome model. In addition, the marginal effect on the observed response is less than the marginal effect on the true response:

$$\frac{\delta Pr(y_i^{observed} = 1|x)}{\delta x} = (1 - \alpha_1) f(x'\beta)\beta < f(x'\beta)\beta \equiv \frac{\delta Pr(y_i^{true} = 1|x)}{\delta x} \quad (4.0.12)$$

To deal with this, this study estimates an adjusted probit model using the methodology of Hausman, Abrevaya & Scott-Morton (1998). An estimate of (α_1, β) is derived by maximising the log-likelihood function:

$$L(a_1, b) = n^{-1} \sum_{i=1}^{n} \left\{ y_i^{observed} ln((1 - a_1)F(x_i'b)) + (1 - y_i^{observed}) ln(1 - (1 - a_1)F(x_i'b)) \right\} \quad (4.0.13)$$

over (a_1, b). I refer to this model the "HAS-Probit" or "Misclassification Probit" estimator.

5 Data And Variables

Data is taken from two business surveys within Nigeria. These are: the Nigeria Bureau Of Statistics (NBS) and the Economic And Financial Crimes Commission (EFCC) Business Survey On Crime And Corruption And Awareness Of The EFCC (2,100+ firms)); and the Enterprise Survey For Nigeria (5,500+ firms). Both NBS and Enterprise surveys include businesses from all 36 states of Nigeria as well as the Federal Capital Territory. Both surveys also ask questions on bribery: the relative frequency with which bribes are paid; and the amount paid.

5.1 Variables Used

All currency figures in this study are measured in '000 Naira. Current profit is measured as the value of total sales minus operating costs and interest payments[5] [6]. Capital stock is calculated as the resale value of machinery, vehicles and equipment.

To measure capital mobility, this paper follows the method used in Svensson [2003] and regresses the resale/replacement ratio on a constant and the average age of capital stock. The residual of the regression represents that amount of the resale/replacement ratio that is not captured by the age of machinery, vehicles and equipment[7]. A positive value indicates that the capital stock is relatively mobile.

Also included as control variables are: a dummy variable indicating whether the government is the principal buyer of the establishment's output; and a variable denoting the number of hours per week that the senior manager spends dealing with federal government; state government; and local government regulations.

The NBS data includes a series of variables denoting operations performed by companies which required interactions with public officials. These are listed in Table 3. These variables serve as measures of the control rights hypothesis since they represent ways in which public

[5] Operating costs are measured as the sum of the following costs: raw materials and intermediate goods; labour; depreciation; rent of land/buildings, equipment and furniture; electricity; fuel; water; transportation (excluding fuel) and communication services.

[6] Loan providing financial institutions include: private commercial banks; state-owned banks and government agencies; non-bank financial instutions; and informal sources of credit.

[7] $\frac{resale_i}{replace_i} = \gamma_0 + \gamma_1 * log(age) + \kappa_i$

Table 2: Data

Survey	ES	NBS
Sample Frame	National Bureau of Statistics; Corporate Affairs Commission; Manufacturers Association of Nigeria; Ministry/Chamber of Commerce and Industry; Nigerian Association of Small and Medium Enterprises	Economic Survey And Census Division (NBS); National Quick Employment Generation Survey (NBS); NBS/CBN/NCC Collaborative Economics Survey
Scope	3 Main Sectors (15 Subsectors)	15 Economic Sectors
Range	All 37 Geo-political Regions	All 37 Geo-political Regions
Total Size	5,544	2,110
Sample Size	2,001	331
(Sub)Sectors	Manufacturing: Food; Garments; Textiles; Machinery & Equipment; Chemicals; Electronics; Non-Metallic Materials; Wood, Wood Products And Furniture; Metal And Metal Products; and Other Manufacturing. Retail. Rest Of The Universe: Information Technology; Construction & Transport; Hotels & Restaurants; Other	Agriculture; Fishing; Mining & Quarrying; Manufacturing; Electricity, Gas & Water; Building and Construction; Wholesale & Retail Trade; Hotels, Restaurant & Tourism; Transport & Communication; Financial Intermediation; Public Administration (Govt); Education; Real Estate, Renting & Business Activity; Health & Social Work ;and Other Community & Social Work
Selection:	Firm Size; Sector Of Activity; Geographic Location	Firm size; Sector Of Activity
Sample Size & Allocation	United Nations (UN) International Standard Industrial Classification (ISIC) Revision 3.1	UN ISIC-Rev.3
Duration:	Sep 07- Feb 08; Jun 08 - Jan 09	Sep 07 - Oct 07

officers might exercise control over the firms operations. This data allows for an analysis into the the propensity to bribe conditional on a specific interaction with a public official; for different types of interactions. This builds on the previous data set by allowing for a heterogeneity in the type of official. Looking at different potential bribe attracting activities allows one to find out which activities are most likely to attract bribes.

5.2 Gauging The Level Of Bribery

The wording on the questions concerning bribery and tax evasion in the Enterprise Survey are indirect. Rather than asking how much a firm pays in bribes the surveys ask how much similar firms pay. This method of asking indirectly is thought to generate more candor on the part of the interviewees about the bribes of their own firm. This is because the indirect nature of the questions reflects any guilt away from the individual firm.

This method of asking indirectly is thought to be useful in gauging the level of bribe paid by the firm due to the false consensus effect [Ross, Greene & House , 1977]. This is the phenomenon that people who engage in a socially undesirable act are more likely to overestimate the prevalence of that act amongst their peers. In this case, firm who pay bribes are more likely to say that similar firms also pay bribes. This helps the current paper to interpret the answer to indirect questions as being representative of the firm itself.

The indirect form of posing questions is similar to that used on the 1998 Enterprise Survey for Uganda[Reinikka & Svensson , 2003]; the Business Environment And Enterprise Performance Survey (BEEPS) on the transition countries [Hellman, Jones & Kaufmann , 2000]; and the North-African Survey of Firms conducted by Université Paris 1[Delavallade , 2011]. This allows

Table 3: Information On Actions Performed By Companies Which Required Them To Meet With Government Officials

Dataset	NBS
Actions	• Cleared Goods Through Customs (Customs) • Obtained Road Worthy Certificates (RWC) • Procurement Of Goods And Services From Government (Gov.) • Obtaining Business Licenses And Permits (Bus. Lic.) • Procurement Of Goods And Services From Private Companies (Priv.) • Getting Clearance For Environmental Or Sanitary Regulations (Enviro) • Residence And Work Permits (Residence) • Vehicle Registrations (Vehicle) • Police Investigations (Police) • Traffic Offences (Traffic) • Contact With The Court (Court)

for comparability between these different studies.

Further support for the validity of the data concerning informal payments is provided by the results of similar surveys carried out within Nigeria and in other countries. In a survey of businesses in Romania [Azfar & Murrell , 2009], there is no difference in the admitting of bribery between firms asked about their own businesses and those asked about "businesses like yours". This lends favour to the argument that no less information is retrieved by asking bribery related questions indirectly.

6 Results - ES

This section discusses the results of the analysis. It provides an analysis on the factors affecting whether or not a company pays a bribe, and the amount that the firm has to pay.

Selected summary statistics for the Enterprise dataset are shown in Table 5. 80% of firms were small in size (5-19 full-time permanent employees); 19% were medium sized (20-99 employees) and 1% of firms had more than 100 employees. The (mean) average age of the firms is 14 years. Less than 1% of the firms were foreign owned but roughly 2% of the sample engaged in some form of international trade[8]. 25% of firms received government provided water in their production process, the figure for electricity was 2%. On average, the establishments operate for 62 hours per week, 3 of which are spent by senior managers dealing with government regulations.

The average annual cost of dealing with requirements imposed by the government was ₦464,000, of which ₦48,500 was spent on external consultants used to deal with regulations. 83% of firms were visited, inspected by, or required to meet tax officials in the previous year, and firms took an average of 16 hours to fill in all forms and requirements to pay local taxes. The average amount of sales that firms reported for tax purposes was 70%, compared with 61% of employees reported for tax purposes. The average level of total employment was 17 workers. 9% of firms

[8] 1.1% of firms solely imported; 0.45% of firms solely exported; and 0.15% of firms engaged in both importing and exporting

Table 4: Variables

Variable Type	Variable Name	Definition
Measures Of Bribery (ES & NBS)	bribe_dummy	Dummy=1 if firm reported a positive amount in bribe, 0 otherwise
	bribe_naira	Amount of bribe in '000 Naira
	ebribe_naira	Amount of bribe per employee (in '000 Naira)
Measures Of Control Rights (ES)	infraserv	Index (0-2) of public goods (water + electricity) acquired from government
	tax_percentage	Percentage of sales declared for tax purposes
Measures Of Bargaining Power (ES)	eprofit	(Sales minus Operating Costs) Per Employee
	Capital_labour	Value of vehicles, machinery, and equipment per employee
	un_sunk_cost	Measure Of Capital Mobility. The residual from: $\frac{resale_i}{replace_i} = \gamma_0 + \gamma_1 * log(age) + \kappa_i$
	alternative_return	un_sun_cost×capital stock
Measures Of Control Rights/Meetings With Public Officials(NBS)	Customs	clearing goods through customs
	RWC	obtaining road worthy certificates
	Gov.	procurement of goods and services from government
	Bus. Lic.	obtaining business licenses and permits
	Priv.	procurement of goods and services from private companies
	Enviro	getting clearance for environmental or sanitary regulations
	Residence	residence and work permits
	Vehicle	vehicle registrations
	Police	police investigations
	Traffic	traffic offences
	Court	contact with the court

had their financial statements checked by an external auditor and 3% of business owners had a university degree.

Average sales declined from 4 years previously to the year before the survey was taken, from ₦11.3 million to ₦8.4 million. The average value of machinery vehicles and equipment for the entire manufacturing sample was ₦3.4 million. The average annual cost of electricity was ₦148,000.

6.1 Bribe Reporting

Results show that 51% of companies admitted to paying a bribe. The sample contained no non-respondents to the bribery related question. Amongst companies that reported a positive bribe, the average amount paid was ₦572,000[9] per year with a median of ₦264,000 (£1050). This corresponds to ₦40,000 per employee (or 6% of operating costs). Looking at the entire sample reduces these averages to ₦294,000; ₦20,000 per employee; and 3.3% respectively. Out of the firms that reported a positive bribe amount; 22% reported this in Naira and 78% reported this as a percentage of sales.

Table 5 shows summary statistics of the main control rights and bargaining variables for all firms. The majority of firms who reported a positive bribe chose to report in terms of sales percentage (802 versus 227). Student's t tests show that firms reporting in terms of sales report significantly higher values of bribe payments, bribe payment per employee, profit and amount of moveable capital than Naira reporters. While Naira reporters declare a larger proportion of their sales for tax purposes and engage in more international trade than sales reporters[10].There are no significant differerences, however, in their number of employees; capital per worker; or

[9] The equivalent of £2270 in October 2007(£1:₦251.97)

[10] Results for bribe; bribe per employee; moveable capital; and tax percentage are significant at the 1% level of significance. The result for international trade is significant at the 5% level.

receipt of public services. The median bribe for the firms reporting bribes in Naira amounts were ₦50,000 whilst this value for sales reporters was ₦390,000.

Chemical manufacturing and wood manufacturing had the highest within-industry percentage of bribe paying firms[11] (57% and 56% respectively). Electronics and garment manufacturing were the least graft-intensive industry subsectors with 17% and 43% firms reporting bribes in each industry respectively[12]. The most bribe-intensive states were Benue; Taraba; and Yobe, with each state having all of its firms admitting to paying some bribe. Lagos and Cross River state had the lowest percentage of bribing firms (19% and 27% respectively).

The correlation matrix (ommitted) shows a statistically significant positive relationship between the receipt of public services ("infraserv") and the payment of bribes ("bribe_dummy"), with a correlation of 0.07 which is significant at the 5% level. The percentage of sales reported for tax purposes ("tax_percentage") is also significantly related to the payment of bribes, with a correlation of 0.1 which is significant at the 1% level. Both variables are also significantly positively correlated with the amount of bribe paid (0.08 [1%] and 0.06[5%], respectively). Profits and size of firm (employees) are also positively correlated with the bribe payment (0.3 and 0.2, respectively, both significant at the 1% level).

6.2 First Stage Estimations

Probit estimations were run to estimate the propensity to bribe. Marginal effects from these estimations are shown in Table 6. The dependent variable in these models is a dummy indicating whether or not the firm paid a bribe. The variable "$infraserv''$ is an index from 0-2 indicating whether or not the company is in receipt of public services from the government. "*tax_percentage*″ denotes the percentage of sales declared, by the company, for tax purposes. These two variables are the two main control rights variables. "$eprofit''$ is profit per employee; "*capital_stock*″ is the resale value of machinery, vehicles, and equipment; and "*alternative_return*″ is the degree of capital mobility (described in Section 5). The baseline model uses only these variables as control variables. The augmented model includes a dummy indicating whether the government is a principal buyer of the output of the company, "*gov_customer*″; and a variable denoting the average amount of time per week spent, by the senior manager, dealing with government regulations, "*regulation_realtime*″. The further augmented model (*Augmented+*) includes regional and manufacturing sub-sector dummies.

The two main control rights variables, $infraserv$ and *tax_percentage*, enter positively and significantly, at the 1% level, in all first stage estimations. The marginal effects suggest that requiring 1 more type of public service from the government is associated with an increased probability of bribing of 6 percentage points. Similarly, every increase in the percent of sales that is reported for tax purposes is associated with an increased probability of bribing of 0.2 percentage points. These results suggest the intuitive idea that interaction with government employees is associated with an increased risk of paying a bribe.

Results for the bargaining variables tend to confirm the conceptual framework. The coefficients on these variables are all relatively small. Displaying them at 3 decimal places renders all of the coefficients to be zero. This suggests that observables such as profit and capital have no impact on whether or not a firm pays a bribe. This goes slightly against the idea that those who pay bribes are the firms who are most willing and able to pay. It seems that the occurrence of bribery occurs randomly amongst the profitable and the less profitable firms. The coefficients on the bargaining variables are all zero and not statistically different from zero, which confirms the conceptual framework since the bargaining variables do not enter into Equation (3.0.1).

[11]Excluding "Other Manufacturing" with a high of 67% of firms reporting graft.

[12]Only 0.3% of the sample (6 firms) were from the electronics manufacturing sector

Having the government, or a government agency, as the principal buyer of the establishment's output is associated with an increased probability of paying of bribe of 0.21 probability points. This effect is significant in the augumented model at the 5% level. Also, an extra hour spent dealign with government regulations is linked with a 1 percentage point increase in the chance of bribing.

All models have significant chi-squared values. A Wald test for the null hypothesis that the coefficients on the control rights variables are equal to zero rejects the null at all traditional significance levels. A similar tests for the bargaining variables fails to reject the null of a zero coefficient on all of the bargaining variables. This provides more support for the idea that the propensity to bribe is not necessarily determined by a firms profit but by required interactions with government officials. A Wald test for the equality of the industry sub-sector dummies fails to reject the null of equality across manufacturing sub-sectors. This suggests that there is not much variation across the different industries in the propensity to bribe. A similar test for the industry subsectors rejects the null hypothesis. Therefore, there appears to be regional variation in the bribing of public officials but no industry variation.

6.3 Second Stage Estimations

Results from the second stage estimation are shown in Table 6. This Table shows the results from using the ordinary least squares; two-stage least squares instrumental variable (2SLS); and general method of moments (GMM) instrumental variables approaches. For the 2SLS estimation the identifying instruments are: a dummies for foreign ownership; a dummy for university education of the owner/majority shareholder; the age of the firm; and annual expenditure on security per employee. For the GMM model the identifying instrument is the sub-sector-location average profit per employee.

The same variables that were used in the first stage are also used in the second stage. The dependent variable in each model is the amount of bribe paid per employee, in '000 Naira. Results show no strong effect of the control rights variables on the amount of bribe paid. The coefficients on $infraserv$ and *tax_percentage* are not statistically significant in the main specifications. The coefficient on profit per employee enters positively and significantly in the main specifications. This gives support to the discussion in Section 3. Results from the baseline and augmented OLS regression suggest that firms that earn ₦1,000 more in profits per employee, pay , on average and ceteris paribus, ₦175 more in bribes. This result is significantly significant, at the 1% level in 8 out of the 9 specifications. Furthermore, the size of this coefficient does not alter much between OLS; 2SLS-IV; and GMM-IV. The coefficient on the measure of expected future profits, capital stock per employee (*capital_labour*), enters positively and significantly, at the 10% level in the baseline and augmented OLS and 2SLS estimations. The size of this effect is approximately 10 times smaler than that of profit per employee which might be explained by the rate at which firms discount the value of future profits. The smaller magnitude of the coefficient, compared to te coefficient on profits, suggests that current profit is more impotant to firms in making decisions on how much to bribe. The lower level of significance might suggest that firms heavily discount the future, which is consistent with an uncertain business environment where bribery exists.

The coefficient on the variable representing alternative return is smaller than *capital_labour* and also enters significantly in fewer models. This might seem to go against the idea that firms consider their outside options when faced with a bribe demanding official, however, this result should be interpreted alongside the previous result that there is not much industry variation in the probability of bribing. Since there is no sub-sector variation in the payment of bribes; a firm's outside option is most likely to involve it having to a pay a bribe in whichever industry it finds itself in. This is one reason why the coefficient on *alternative_return* only enters significantly in 3 models. A further explanation is provided when an F-test for the equality of industry sub-sector dummies is conducted in the *Augmented+* model. This test fails to reject the null of equality of the bribe amount across different industry sub-sectors. This result suggests that the firm's outside options would involve it paying roughly the same amount of bribe payment to another public official in a different industry, therefore the small and weakly significant coefficient on the variable for *alternative_return* can be explained by the fact that the outside options are not too dissimilar from the present option.

The coefficients on the government as the primary purchaser of the company's output; and the amount of time spent dealing with government regulations enter insignificantly into the models. This supports the conceptual framework and adds more weight to the idea that the amount of bribe paid is solely a function of the firms ability to pay; willingness to pay; and outside options rather than the nature of a firm's meetings with public officials. An F-test on the regional dummies rejects the null of equality; suggesting that there is regional variation in the amount of bribe paid. The first-stage F-Statistic is significant in all IVs; suggesting that the instruments are not weak. A Durbin-Wu-Hausman test of endogeneity fails to reject the null of exogeneity of the profit variable. This suggest that one can have confidence in the OLS estimates in this Table. All of these models are statistically significant.

7 Results - NBS

This section augments the previous results by including data from the NBS survey into the analysis. The previous analysis does not distinguish between the reasons for bribery but instead specifies a number of general activities that might require a bribe. Firms were asked whether payments were made with regard to "customs, taxes, licenses, regulations, services etc". On one hand, asking a question in this manner might attract a higher estimate of the proportion of bribing firms i.e. asking if a firm paid a bribe for a number of activities might increase the reporting of bribery. On the other hand, this measure does not distinguish between bribes paid for different activities. Therefore, any conclusions based on this data might give a biased view of the business environment in Nigeria: a large proportion of firms might have paid a bribe in order to avoid punishment for an offence committed, rather than to bypass cumbersome regulation. In order to get a better view of the nature of bribe payments , the NBS data asks specific questions concerning what bribes were paid for. This data allows for an analysis into the processes which attract the highest proportion of bribes.

Table 8 presents summary statistics for the NBS dataset. This table shows information on meetings with public officials; and bribing of public officials for: all firms; those who met with public officials; those who bribed public officials. In this setup, a firm manager has to met with a public official in order to bribe a public official. Therefore, not meeting a public official is a perfect predictor of not bribing; and bribing an official implies that a meeting must have taken place. There are a total of 11 meeting types asked about in this dataset, these are shown in Table 3. Results show that 37% of firms met with a public official. Managers who met with an official did so, on average, for 4 out of the 11 reasons asked about in the questionnaire. Out of the managers who met with an official 36% of them paid a bribe to an official. Bribing firms met with an average of 4 officials and bribed 3 officials. The mean bribe value for the sub-sample of bribing firms is ₦3,400.

Probit estimations were run on the propensity to bribe. The impact effects are shown in Table 9. The dependent variable in this table is a dummy equal to 1 if the firm admitted paying any type of bribe (specific or general). The variables in the table are dummy variables denoting the different types of officials that the firms met with. These can be treated as control rights variables with the exception of the variable denoting procurement of goods and services from private companies. The models also control for the size of firm; age; and foreign ownership. Models 1 to 11 show the partial impact effects of each control rights variable on the probability of paying a bribe; the full specification includes all control rights variables.

All variables enter positively and significantly at the 1% level in their respective partial effects models, with the exception of the variables representing: the procurement of goods and service from private companies; and contact with the court. Thus, in line with the conceptual framework, there is a positive relationship between meeting a public official and paying a bribe. The largest impact effect is found in model 10 which measures the partial effect of meeting with officials because of traffic offences on the propensity to bribe. Doing so leads to an increased probability of paying a bribe equal to 0.603 probability points, on average and ceteris paribus. The second largest impact effect (0.375) is associated with meeting officials for police investigations. These results tend to be consistent with the results of surveys and research within and outside Nigeria which suggests the police force, who also deal with traffic offences, is one of the most corrupt public institution. The coefficient on the variable for traffic offences maintains its sign and significance when entered into the full specification. A Wald test of equality of the coefficients rejects the null of equality at the 1% level, giving more weight to the argument of heterogeneous officials.

8 Robustness Checks

The Section shows the results of the misclassification adjusted probit model for the first stage estimation of the ES data; and for the estimation of the NBS data. Table 10 shows results for the marginal effects from the baseline probit specification; and the baseline HAS-Probit specification using the ES data. The marginal effects do not change by a relatively large amount. As expected, the marginal effects on the probability of bribing from HAS Probit model are larger than the ordinary probit model. The model remains significant when allowing for misclassification. The log-likelihood function returned an estimate of the probability of observing a false negative of 21.9%. In other words, the probability of observing a report of zero bribes when in fact the company did pay a bribe is 0.219.

Impact effects from the HAS-Probit model on the NBS data are shown in Table 11. All of the coefficients have the same sign and the majority of them keep their significance. Out of the significant coefficients, the ones relating to traffic offences and police investigations once again have the largest magnitudes. The results from prevously are seen in the HAS-Probit model as the coefficient for traffic remains significant and is also the largest coefficient in the full model.

9 Comparing The Two Datasets

Firms in the Enterprise Survey showed a greater willingness to report bribery than those in the NBS survey. 51% of firms in the ES reported a positive bribe payment compared to 27% of the NBS sample. When focusing on manufacturing firms, the data seems to tell a similar story: 51% of ES manufacturers reported paying a bribe compared to 23% of NBS manufacturers (Table ommitted).

Focusing on the average level of bribe payments for all firms and bribe paying firms: the average bribe payment for the ES full sample (All Industries) was ₦293,400. Focusing on bribe paying firms alone raises this average to ₦562,200. There was also a wide disparity in the average reported bribe payments between companies who report in terms of the absolute Naira amount and those who choose to report their bribe payments as a percentage of sales. Focusing on firms who reported paying a bribe the average reported bribe payments amongst sales reporters was ₦690,000; whereas those who revealed their bribe as a Naira figure reported paying, on average, ₦73,700. The distribution of bribe payments for firms in the NBS sample appears to be closer to that of the ES Naira reporters: the average reported bribe payment for this sample of firms is ₦53,400. These results are also seen when looking solely at the manufacturing industry in Nigeria. Average bribe payments for bribing sales reporters, Naira reporters, and NBS firms , respectively, are: ₦710,300; ₦85,500; and ₦77,900.

The regional distribution of bribe incidence and the average bribe payments amongst bribing firms per state is shown in Figure 1. The upper part of the diagram shows the proportion of bribe reporting firms across different states in Nigeria for all firms of the ES sample. Results indicate a relatively higher prevalence of bribing firms in the South-South region of Nigeria. These include Rivers, Imo and Akwa Ibom and these results are consistent between both datasets. Kogi State also has a relatively high prevalence of bribery. Focusing on the average bribe payments for bribe reporting manufacturers, companies in Adamawa appear to consistently report a higher bribe payment in both samples.

9.1 Perceptions Versus Reality

Perception based indicators of corruption can suffer from bias [Carlin & Seabright , 2007]. More productive companies have a higher valuation of the business environment than less productive firms. Accordingly, any constraint to the business environment serves as a higher cost to their operations compared with less productive companies. Following from this, relatively more productive firms are more likely to complain about constraints to the business environment than less productive ones. Therefore creating a bias in perception indices of the state of the business environment.

One possible solution to this, in the case of bribery, is to compare subjective reports on the extent of corruption to the actual reported bribe payments. If all firms face the same business environment then, in the absence of misreporting and bias, companies in areas where bribery is more pervasive should report this in their subjective valuations of the business environment.

Companies in the Enterprise Survey were asked: "Do you think that the following present any obstacle to the current operations of your establishment?" with "corruption" being one of the options.[13]

Responses to these questions show some evidence that businesses are revealing something when they give subjective evaluations of the business environment. Only 39% of those who said that corruption presented "no obstacle" to business operations paid a bribe to deal with business regulations whereas 69% of those who reported that corruption posed a "very severe obstacle" to operations reported paying a bribe. The values for the proportion of bribing firms increases as one moves from 'no obstacle' to 'very severe obstacle'. The proportion of bribing firms decreases as one moves from the 'moderate obstacle' group to the 'major obstacle' group, however, this difference is not statistically significant at the 10% level. This pattern is also reproduced in the NBS dataset.

[13] To be sure, the term "corruption" encompasses a number of acts, so companies might have been referring to bribery amongst other things when responding to this question. However, the data suggests a positive relationship between the occurrence of bribery and the other elements that come under the term "corruption".

9.2 Instigator Of The Bribe Transaction

Finally, Table 12 helps to shine light on the instigator of the typical bribery transaction. This is done by using a set of categorical response questions which ask the firms how frequently bribes are: 1) demanded from; and 2) offered to; public officials. Firms were given a choice of responses: never happens; not very frequent but not unusual; fairly frequent; and very frequent. The base category used in Table 12 is “never happens”. The first three columns of coefficiets show results from the model that uses the offering of gifts as the dependent variables; the second set of coefficients, on the right hand side, show results from the model describing the determinants of bring asked to pay a gift to a public official.

Committing a traffic offence is associated with an increased relative risk of reporting that firms offer bribes to public officials “very frequently” relative to reporting that “this never happens”. In addition to an increased risk of offering an official an informal payment, being involved in a traffic offence increases the log of the relative-risk of reporting that officials demand bribes very often relative to not at all. This result also holds for the other two categories. The coefficients on traffic offences are, on average, larger and have greater statistical significance than the other coefficients. It therefore seems that traffic offences attract bribe demands from public officials and propel bribe offers from firms. Furthermore, the coefficients in the model describing the determinants of being asked to pay a bribe are larger and more statistically significant than the coefficients in the model that describes the offering of bribe payments by firms. Therefore, it appears that, according to firms, public officials demand bribes to a greater extent than firms offer bribes; however, there is evidence to suggest that both phenomena are present in the business environment in Nigeria.

10 Conclusion

This paper has shown evidence for both the control rights hypothesis and the bargaining hypothesis amongst manufacturing companies in Nigeria. Despite the potential sensitivity of the topic, various methods have been used in order to extract honest responses about bribery from firms. Whilst still potentially measured with error, these responses assist in the analysis of the nature of bribe payments amongst Nigerian firms.

The occurrence of bribery seems to be positively related to interactions with government officials. Results also suggest that the size of the bribe is determined by factors representing a firm’s ability to pay and outside options. These findings are robust to different econometric specifications. Results point to the notion that firms pay bribes because they desire items and/or services in order to carry out their business,which sometimes require them to pay informal gifts in order to either receive them or speed up the process of receiving them [Leite & Weidemann , 2002]. In the case of Nigeria, 65% of manufacturing firms state that the government’s interpretation of laws and regulations are consistent and predictable. 51% of firms report a positive bribe amount that is required in order to speed the process of regulations.

By distinguishing between the different purposes for which a bribe was paid, this investigation was able to analyse which activities were more likely to attract bribes. The data presented in the preceeding analysis builds on the literature that analyses specific reasons for these payments.

Varaibles denoting interactions with public officials were found to be positively related with the propensity to pay a bribe. Firm specific characteristics such as profit and capital stock were found to be relatively good indicators of the level of bribe paid. On average, firms with higher profits pay larger bribes. Earning 1,000 Naira (per employee) more, is associated with an increased bribe payment of 175 Naira (per employee), on average and ceteris paribus. Evidence was found for regional heterogeneity in the payment and size of bribe after controlling for observables. Regions with higher probability of bribe payment seem to have a lower average bribe payment (consistent with Shleifer & Vishny (1993); Svensson (2003)). Furthermore, the propensity to pay a bribe, conditional on meeting a public official, depends on which type of public official a firm meets with (consistent with Hunt (2006); Hunt & Laszlo (2012)). Meeting with an official because of a traffic offence has the greatest impact effect on the probability of paying a bribe; and the relative-risk of being asked to pay a bribe by a public official.

Further work can build on this study by investigating whether informal payments have a significant effect on the future profitability and competitiveness of companies. This will allow for a better interpretation of the effect that expected future profits has on the level of bribe paid. Work that investigates the effect of competitors paying bribes on the firm's profitability and propensity to bribe would also add to the analysis of the supply of bribes.

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A Appendix

Table 5: Summary Statistics

Variable	Statistic	All Firms	Bribe=0	$Bribe > 0$
bribe_naira	Mean	294	0	572
	Median	8	0	264
	Std. Dev.	652	0	816
ebribe_naira		20.6	0.0	40.0
		0.5	0.0	22.2
		49.6	0.0	63.3
employee_total		17	18	16
		12	13	12
		16	18	14
eprofit		158.7	155.3	161.8
		90.0	77.8	100.1
		216.8	211.8	221.4
capital_labour		230.2	190.9	267.2
		100.0	75.0	125.0
		718.8	544.4	850.0
un_sunk_cost		-0.88	-0.88	-0.89
		-0.88	-0.88	-0.89
		0.03	0.02	0.03
infraserv		0.29	0.25	0.32
		0.00	0.00	0.00
		0.50	0.48	0.51
tax_percentage		69.6	66.1	72.8
		75.0	70.0	75.0
		27.4	28.2	26.2
N		2001	972	1029

In each column, for each variable, the table reports the mean, median and standard deviation for each (sub)sample. The last row details the number of observations for each (sub)sample.

Figure 1: Proportion Of Bribing Firms; And Average Bribe Amounts For Bribing Firms, By Region

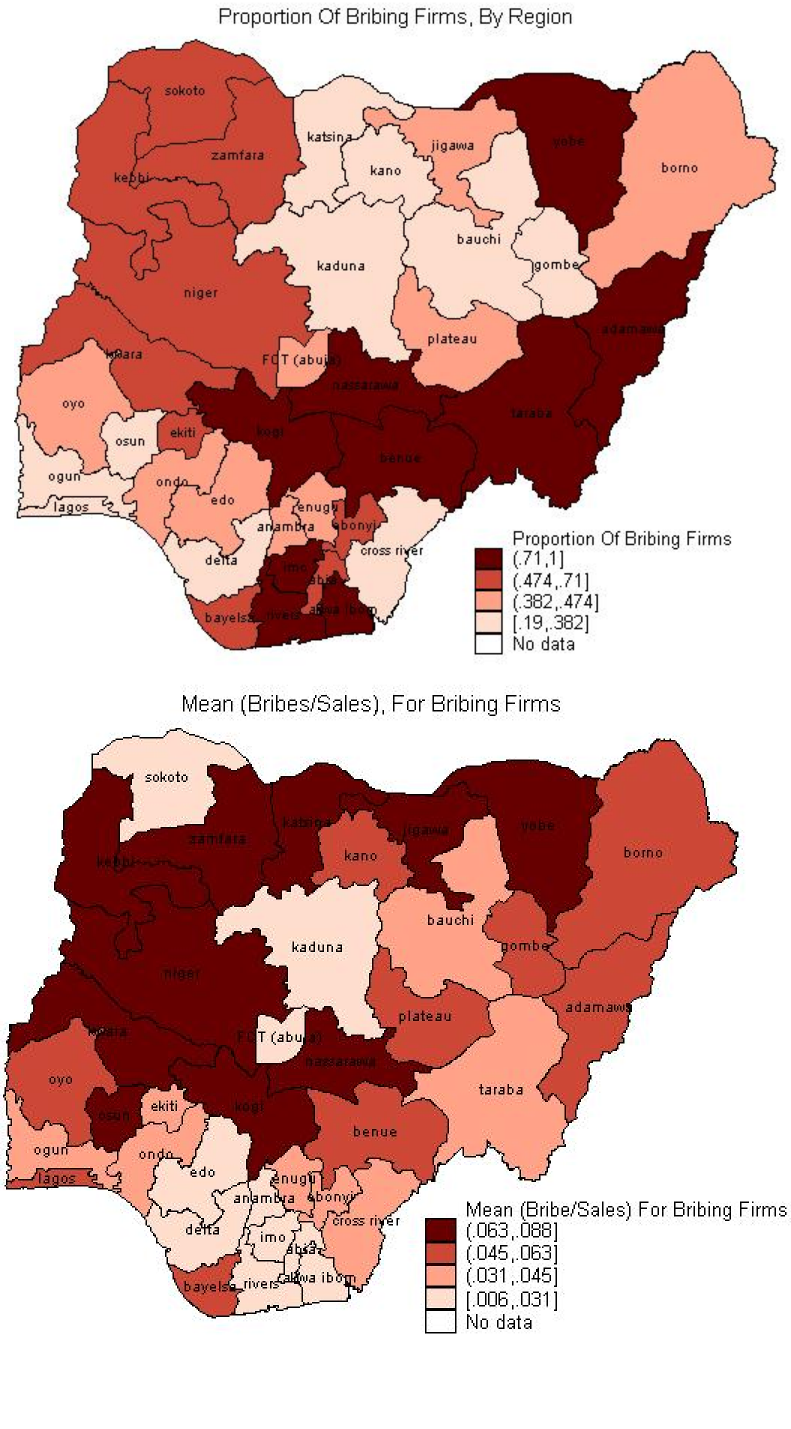


Table 6: Marginal And Impact Effects From First Stage Probit Regressions

	Baseline	Augmented	Augmented+
infraserv	0.067***	0.060***	0.070***
	(0.023)	(0.023)	(0.027)
tax_percentage	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.001)
eprofit	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
capital_stock	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
alternative_return	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
gov_customer (d)		0.210**	0.128
		(0.089)	(0.110)
regulation_realtime		0.007**	0.012***
		(0.003)	(0.003)
Sub-Sector Dummies	NO	NO	YES
Region Dummies	NO	NO	YES
Pseudo R-squared	0.015	0.025	0.150
Observations	2001	2001	1891
Log-Likelihood	-1365.0	-1351.0	-1114.1
Chi-Squared	40.7	65.4	305.3
P Value	0.000	0.000	0.000
Control=0 (Chi2)	37.53	38.61	13.60
P	0.0000	0.0000	0.0011
Bargaining=0 (Chi2)	2.21	2.05	1.02
P	0.5303	0.5628	0.7958
Industry-Chi2	-	-	8.87
Industry-P	-	-	0.2618
Region-Chi2	-	-	219.93
Reg-P	-	-	0.0000

$*p < 0.10, **p < 0.05, ***p < 0.01$

Dependent variable is a dummy=1 if firm reported a positive bribe payment; 0 otherwise. (d) for discrete change of dummy variable from 0 to 1

Table 7: Results - Regressions On The Amount Of Bribe

	Base	(IV-2sls)[14]	(IV-gmm)[15]	Aug	(IV-2sls)	(IV-gmm)	Aug+	(IV-2sls)	(IV-gmm)
infraserv	-3.536	-4.531	-0.358	-3.549	-4.336	-0.341	3.218	2.133	5.696*
	(3.518)	(4.573)	(3.204)	(3.543)	(4.525)	(3.200)	(3.581)	(4.233)	(3.257)
tax_percentage	-0.077	-0.075	0.157***	-0.060	-0.058	0.141***	-0.055	-0.049	0.000
	(0.052)	(0.054)	(0.055)	(0.054)	(0.055)	(0.054)	(0.056)	(0.058)	(0.055)
eprofit	0.175***	0.201***	0.156***	0.175***	0.195***	0.150***	0.160***	0.227***	0.063
	(0.039)	(0.072)	(0.033)	(0.039)	(0.068)	(0.033)	(0.041)	(0.066)	(0.040)
capital_labour	0.017*	0.015*	0.020	0.018*	0.016*	0.021	0.012	0.007	0.020
	(0.009)	(0.009)	(0.012)	(0.010)	(0.009)	(0.013)	(0.008)	(0.006)	(0.014)
alternative_return	0.001*	0.001	0.001	0.001*	0.001*	0.001	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
gov_customer				18.656	18.385	21.528	19.002	17.637	23.201
				(16.169)	(15.710)	(16.456)	(14.825)	(13.345)	(16.591)
regulation_realtime				-0.493	-0.484	-0.206	0.093	0.057	0.343
				(0.318)	(0.321)	(0.333)	(0.386)	(0.408)	(0.386)
Constant	17.367***	13.579		20.182***	17.391		14.778*	7.779	
	(5.996)	(11.027)		(7.213)	(11.162)		(8.142)	(10.141)	
Sub-sector Dummies							YES	YES	YES
Region Dummies							YES	YES	YES
F	6.278			6.610			.		
$H_0 : Exogenous$		.286	.3823		.193	.452		2.25	0.000
P		.593	.5364		.661	.502		.134	1.000
First Stage F		85.79	119.85		57.81	67.82		25.16	15.73
Adjusted R-squared	0.402	0.394		0.404	0.399		0.489	0.439	
Observations	1029	1029	1029	1029	1029	1029	1029	1029	1029
Ind-F							1.39	8.93	9.59
Ind-P Value							0.2042	0.2574	0.2128
Reg-F							6.47	161.68	275.78
Reg-P Value							0.0000	0.0000	0.0000

Dependent variable is bribe amount in '000 Naira

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 8: Summary Statistics Of Bribery And Meeting With Public Officials - NBS Data

	(1)	(2)	(3)
	Bribery/ Meeting With Official		
	All Firms	Met With An Official	Bribed An Official
Met With An Official	0.37	1	1
(Mean) Average Number Of Types Of Officials Met With	1.66 (2.72)	4.43 (2.74)	4.20 (2.50)
Bribery Episode	0.14	0.36	1
(Mean)Number Of Types Of Bribery Episodes	0.44 (1.39)	1.16 (2.07)	3.20 (2.31)
Observations	331	124	45
(Mean)Value Of Bribes ('000 ₦)(₦)	0.616 (4.56)	1.65 (7.36)	3.43 (9.49)

The unit of observation is the firm. Standard deviations are in parentheses.

Table 9: Probit Estimations On The Propensity To Bribe - NBS Data (Impact Effects)

	0	1	2	3	4	5	6	7	8	9	10	11	full
Customs		0.309***											0.153
		(0.082)											(0.107)
RWC			0.226***										-0.162**
			(0.068)										(0.067)
Gov.				0.308***									-0.047
				(0.111)									(0.084)
Bus. Lic.					0.223***								0.043
					(0.077)								(0.100)
Priv.						0.140							-0.025
						(0.104)							(0.098)
Enviro							0.311***						0.094
							(0.076)						(0.107)
Residence								0.168**					-0.143***
								(0.081)					(0.052)
Vehicle									0.333***				0.317**
									(0.068)				(0.127)
Police										0.375***			0.142
										(0.095)			(0.125)
Traffic											0.603***		0.659***
											(0.075)		(0.096)
Court												0.045	-0.154***
												(0.102)	(0.041)
Pseudo R-squared	0.098	0.150	0.135	0.126	0.127	0.104	0.153	0.112	0.176	0.151	0.297	0.098	0.383
Log-Likelihood	-145	-137	-139	-140	-140	-144	-136	-143	-132	-136	-113	-145	-99
Chi-Squared	34.2	50.1	49.2	46.4	45.6	39.7	51.9	37.5	61.9	46.8	84.4	34.1	104.6
Reg-Chi-Squared	19.17	21.78	20.91	23.87	19.20	20.59	19.85	19.34	22.45	18.69	30.11	18.82	39.12
Reg-P Value	0.4	0.3	0.3	0.2	0.4	0.4	0.4	0.4	0.3	0.5	0.1	0.5	0.0

287 Observations. Dependent variable is a dummy variable equal to 1 if the firm reporting paying a bribe; 0 otherwise. Control vars include: size of firm, age of firm, foreign ownership.

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 10: Misclassification Probit - Marginal Effects

	Baseline	Misc. Baseline
infraserv	0.067***	0.086**
	(0.023)	(0.095)
tax_percentage	0.002***	0.003***
	(0.000)	(0.002)
eprofit	0.000	0.000
	(0.000)	(0.000)
capital_stock	-0.000	-0.000***
	(0.000)	(0.000)
alternative_return	-0.000	-0.000***
	(0.000)	(0.000)
α_1	-	0.219
Pseudo R-squared	0.015	
Observations	2001	2001
Log-Likelihood	-1365.0	-1360.1
Chi-Squared	40.7	26.9
P Value	0.000	0.000

Dependent variable is a dummy variable equal to 1 if the firm reporting paying a bribe; 0 otherwise.

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 11: Misclassification Probit (Impact Effects)

	0	1	2	3	4	5	6	7	8	9	10	11	full
Customs		0.309***											0.212*
		(0.209)											(0.491)
RWC			0.421										-0.225*
			(0.779)										(0.484)
Gov.				0.624									-0.065
				(1.319)									(0.949)
Bus. Lic.					0.223***								0.060
					(0.195)								(0.489)
Priv.						0.449							-0.035
						(1.139)							(0.576)
Enviro							0.311***						0.130
							(0.194)						(0.485)
Residence								0.168**					-0.198
								(0.213)					(0.696)
Vehicle									0.390				0.440***
									(0.796)				(0.465)
Police										0.375***			0.197
										(0.236)			(0.584)
Traffic											0.822***		0.914***
											(0.643)		(0.642)
Court												0.045	-0.214***
												(0.301)	(0.650)
α_1		0.0000	.464	.506	0.0003	.0000	.0000	.147	.0000	.266	.0000	.0000	.279
Log-Likelihood	-167	-157	-160	-162	-161	-165	-157	-164	-153	-157	-134	-167	-121
Chi-Squared	8.60	27.09	3.69	6.33	20.52	4.25	26.96	15.18	2.72	27.15	15.46	9.92	26.23
P	0.0351	0.0000	0.4493	0.1755	0.0004	0.3730	0.0000	0.0043	0.6065	0.0000	0.0038	0.0418	0.0242

300 Observations. Dependent variable is a dummy variable equal to 1 if the firm reporting paying a bribe; 0 otherwise. Control vars include: size of firm, age of firm, foreign ownership.

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 12: Relative Risk Ratios For The Instigator Of The Bribe Transaction

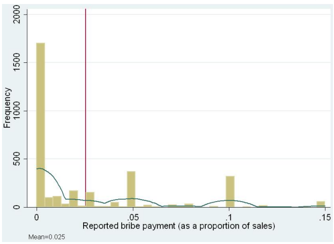
Dependent Variable:	"A Firm Offers Gifts/Money To A Public Official"			"A Public Official Asks a Firm For Gifts/Money"		
	"not very frequent but not unusual"	"fairly frequent"	"very frequent"	"not very frequent but not unusual"	"fairly frequent"	"very frequent"
Customs	4.387**	1.333	1.144	6.250**	3.904	0.999
	(3.171)	(1.330)	(0.916)	(5.656)	(3.365)	(0.928)
Bus. Lic.	0.712	0.726	4.199*	0.494	0.845	9.894**
	(0.657)	(0.618)	(3.422)	(0.423)	(0.780)	(10.879)
Vehicle	0.152**	0.086***	0.477	0.055***	0.248	0.118**
	(0.129)	(0.073)	(0.315)	(0.052)	(0.239)	(0.126)
Police	2.956	7.600*	3.433	0.651	0.713	0.092
	(3.157)	(8.140)	(4.667)	(0.614)	(0.655)	(0.153)
Traffic	7.187**	9.497***	20.563***	11.072***	12.631***	108.439***
	(5.567)	(6.516)	(15.546)	(8.662)	(9.457)	(119.588)
Court	7.308*	0.254	0.769	10.483*	25.945***	7.328
	(8.217)	(0.396)	(1.094)	(12.722)	(28.017)	(10.948)
Constant	0.043**	0.239	0.000	0.169	0.379	0.000***
	(0.062)	(0.257)	(0.000)	(0.185)	(0.494)	(0.000)

Base category: "never happens". Control vars include: size of firm, age of firm, foreign ownership, regional dummies, RWC, Gov., Priv., Enviro, and Residence.

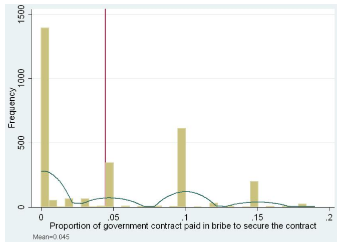
$*p < 0.10, **p < 0.05, ***p < 0.01$

Figure 2: Reports Of "Similar Firms"

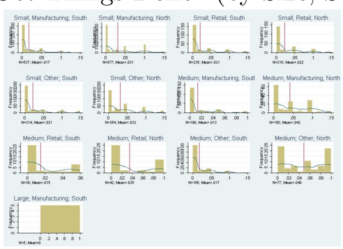
Informal Payments To "Get Things Done"



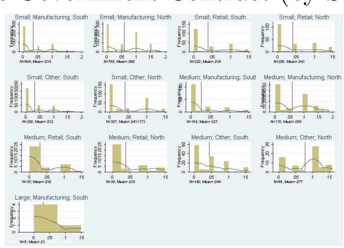
Informal Payments To Acquire Government Contract



Payments To "Get Things Done" (by Size; Sector & Region)



Payments To Acquire Government Contract (by Size, Sector & Region)



Legalize, Tax, and Deter: Optimal Enforcement Policies for Corruptible Officials

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Abstract

Corruption of law enforcers remains a significant problem in many countries. We propose a model where deterrence of a harmful activity (such as trade in illicit drugs) is hindered by corruption, but standard anti-corruption policies might be too costly to implement. We show that an alternative tax-and-legalize policy can yield significant benefits, especially in poor countries with weak institutions and for activities that are not too harmful. Using a tax-and-legalize scheme, the government reduces the cost of implementing standard anti-corruption policies, easing the fight against corruption. However, a tax-and-legalize policy could increase the equilibrium number of harmful activities.

JEL Classification: D73, K42, O10, H21

Keywords: legalization, permits, law enforcement, corruption, incentives, self reporting, leniency program, collusion.

1 Introduction

The corruptibility of law enforcers remains a significant concern in many developing and advanced economies. Among the possible anti-corruption policies, the economic literature has mainly focused on compensation schemes that penalize corruption and reward honest behaviors (Mookherjee and Png [1995], Mishra [2002], and Bose [2004]). While these policies

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have the potential to effectively limit corruption, their implementation has proven to be unsatisfactory in many countries (Transparency International [2010]). What could explain these failures? A reason may be that stamping out corruption is costly, and in some countries tolerating it might be socially optimal (Besley and McClaren [1993], Acemoglu and Verdie [2000], and Baç, and Bag [2006]).

The primary objective of this paper is to show that legalization is useful in cases where traditional anti-corruption policies are costly to implement. In a setting where individuals engage in harmful activities and bribe officers to avoid being sanctioned, we study the effect of implementing a tax-and-legalize scheme. This scheme allows individuals to freely undertake the sanctioned activity in exchange for the payment of a tax or reduced fine. We will show that legalization changes the enforcement problem, turning it from one of apprehension of sanctioned acts, to one of detection of tax evasion. However, the potential problem of corruption remains: just as before, tax evaders can bribe audit officers. Yet, this paper will demonstrate that legalization in some instances reduces the cost of implementing an effective (and otherwise expensive) anti-corruption scheme, thus solving the corruption problem.

To show this point, we build a simple model of enforcement in which individuals generate a social harm when engaging in a certain activity (such as pollution or dealing with illegal drugs) that provides them with a private gain. The government hires officers to monitor the population and fine miscreants, and can decide whether to allow bribery to take place or, through appropriate incentives, ensure that officers never accept bribes. We model the enforcement problem such that bribes lower deterrence but are otherwise efficient: they generate a transfer from miscreant to officers that avoids socially costly bureaucracy and red tape. This setup allows our model to obtain many expected predictions that conform with the existing literature. For instance, we find that poorer countries are more likely to adopt corrupt enforcement, because anti-corruption policies are more expensive at lower income levels. We also find that countries that are more tolerant of corruption or with high red tape levels are more likely to adopt corrupt enforcement regimes. More surprisingly, we find that the corruptibility of officers imposes significant welfare costs precisely in countries with low levels of wealth, where corruption is most likely to occur. At higher levels of wealth, on the other hand, the corruptibility of agents matters less and less for welfare: the tools available to the government are sufficiently flexible that corruption avoidance is inexpensive.

Given this model, we analyze the effect of a tax-and-legalize policy. Individuals have the option to freely engage in the harmful activity, then pay a tax to the government. Since tax avoidance is an option, tax evaders would still face sanctions once audited, and therefore can still attempt to bribe officers. Thus, the corruption problem does not go away with a tax-and-legalize scheme. However, those individuals who do pay the tax have acted legitimately, and therefore need not bribe the tax enforcers. Whenever one individual pay the tax, there is one less anti-corruption incentive that needs to be paid out. This makes anti-corruption policies sufficiently cheap that, as it will be shown, are completely and comprehensively adopted in a legalized regime. This is particularly useful when such policies are otherwise costly, which occurs at low levels of wealth in the model, precisely where corruption is the preferred policy. Our welfare predictions are therefore quite stark: poor countries where an illegal activity begets corruption should legalize, *regardless of how tolerant of corruption that country is.*

The use of a tax-and-legalize scheme does lead to a potentially unpleasant effect: in general, we find that more individuals engage in the socially harmful activity when it is legal, even when the activity is appropriately taxed. Unlike most prior (mostly empirical) literature, this is not due to changes in the demand function of consumers[1], or motivated by the introduction of a revenue concern to the government: our model keeps both demand function and government revenue concern constant. Instead, the reason for the increase in the harmful activity is that, absent legalization, there is *too much* enforcement (something that was also previously noted by Mookherjee and Png [1995]). Correcting this over-enforcement is a property of legalization that, in a political economy context, could be considered *controver-*

[1] Empirically, legalization has been found to increase the quantity demanded of the previously illegal good (Saffer, and Chaloupka, (1999), DiNardo and Lemieux (2001), and Anderson and Rees (2011)).

sial: while society is better off with higher levels of the harmful act and a lower government budget, individual voters who easily observe the first and not the latter might reject legalization. Over-enforcement is less likely to occur at very low levels of wealth and for activities that are not too harmful, suggesting that legalization could be more appealing in developing countries and for lesser illegal activities.

The theory presented here is empirically relevant, particularly (but not only) for the regulation of illicit drugs. Many poor countries have already legalized narcotics that are illegal elsewhere. For instance, *chat*, a narcotic plant, is freely traded, taxed, and consumed in Ethiopia, Yemen and Somalia. It remains illegal elsewhere. Bolivia has legalized the sale and consumption of coca *leaves*, although more processed and harmful forms (a category that includes cocaine) remain illegal. The call for broader legalization of other illegal drugs is being increasingly made in policy circles by prominent figures concerned with corruption. In 2010 former president of Mexico Vincente Fox argued in favor of drug legalization, in part on corruption grounds. The presidents of both Bolivia and Uruguay are actively pursuing more lax legalization policies, against the wishes of many western countries.[2]

There are other instances of legalization or self reporting policies in areas where the possibility of corruption is great.[3] As part of a larger anti-corruption push, off-track betting was legalized in Hong Kong in the seventies; the legalization eliminated an important source of bribes for the police force, and police corruption was eliminated shortly after (Klitgaard [1988]). While big game hunting is generally illegal in Africa, countries such as Malawi, Tanzania and Zambia have adopted hunting permits as a form of legalization for a crime –

[2]The consumption and trade of cannabis has been legalized in many Western countries and US states too; such legalization is generally driven by considerations not directly considered here, such as incarceration policies. Nonetheless, our model can explain this evidence. Our results suggest that legalization can be optimal even in countries where effective anti-corruption policies are in place, especially for activities that are not too harmful.

[3]Among the various voices in the debate over legalization of things other than drugs, it is worth mentioning Basu (2011) who recently suggested legalizing bribe *giving*, while keeping sanctions on bribe *taking*. He observed that, when the entire punishment from corruption is concentrated on the bribe taker, the bribe giver has an incentive to report the bribe exchange. Anticipating this, the bribe taker will be much less inclined to take the bribe in the first place. While we model legalizing the underlying activity and not the act of bribing, both models hinge on providing an alternative outside option to the bribe giver.

poaching – that is difficult to control.[4]

More broadly, the scheme we present here extends beyond legalization, and fits into a general class of models where corruption is reduced by empowering individuals to bypass officials (Motta [2012], and Burlando and Motta [2013]). Such schemes are becoming increasingly prevalent. In 2005, India introduced a Freedom of Information Act (the RTIA), which allows citizens to inquire about any governmental activity–including the status of a person's own permit applications. Peisakhin (2012) and Peisakhin and Pinto (2010) showed in randomized trials that RTIA requests provide an alternative way to petition for a permit, which ultimately reduces bribe payments. Private companies in developing countries also use such schemes to get around their own corruptible employees. In India, the *tatkal* system was introduced by the phone company to provide people with an alternative to paying bribes for quick phone line installations. The Bharat Sanchar Nigam company guaranteed speedy connections to those willing to sign up and pay into the program. The same *taktal* system was later adopted by the railways as a way for customers to avoid long waiting lists or paying bribes to intermediaries for a quick ticket. In many instances, self reporting can become operational following a technological innovation. In Tanzania, customers could consume electricity for years without ever paying their bills. This was quite common until TANESCO introduced 'smart' electronic meters which require payment before supplying electricity, bypassing the corrupt workers. This system was borrowed from the cell phone industry and has been successfully adopted in the water, telecommunications and trash disposal sectors.[5]

The rest of the paper is organized as follows: after a discussion of the current theoretical literature, section 2 discusses the model of enforcement sans corruption; section 3 studies the effects of corruption; section 4 introduces the tax and legalize scheme. Section 5 concludes.

[4]That some legalization of wildlife hunting and trade can be helpful and beneficial for conservation is a concept that is not lost for several environmental groups. In their 2008 joint report, TRAFFIC and the WWF state that "Policies that criminalize the wild meat trade have not been effective to bringing it under control...greater consideration of alternative management scenarios, including legalizing hunting and trade of certain wild species for meat is therefore required" (Roe, 2008).

[5]Top-up systems or pre-paid services are different from self reporting in one important aspect: the client has no choice but to pre pay if he wants the service. In law enforcement, miscreants always have a choice not to pay.

Relation to the literature There is a growing literature on the economics of corruption and legalization in law enforcement, which is often referred to as *self reporting*. Under self reporting, the harmful activity is illegal, and remains so. Kaplow and Shavell (1994) introduced the idea of self reporting in law enforcement;[6] in their model, self reporting saves money by reducing the number of officers needed to monitor the population.[7] These cost savings hinge on the enforcement agency being able to separate self reporters from the rest of the population, which is not generalizable to many contexts where legalization would be useful. Polinksy and Shavell (2001) consider a setup similar to ours but do not explicitly model the source of the deadweight losses from corruption, and do not explore the role of self reporting in corruption.[8]

The model we present here can be thought of as a self reporting model, because individuals carry out the harmful acts *first*, and only *later* declare the acts through the payment of the tax. An alternative legalization scheme would have an individual having to purchase a *permit* from a bureaucrat *before* engaging in the sanctioned activity. Technically, our results would hold irrespective of the timing. However, in the context of the permit, the corruption problem could arise anew: a bureaucrat could decide to hold up the issuing of the permit in exchange of a bribe (see Bardhan [1997] for a thoughtful discussion). This problem is avoided by our scheme because the acts can be reported after they have been committed. In practice, we believe that this distinction is becoming less important: creative use of freedom of information acts, as well as new technologies that allow for the remote application of taxes, levies, and permit requests, help avoiding bureaucratic holdup. We also sidestep another important distinction between legalization and self reporting, namely the psychological effect of making an illegal activity legal (what Miron and Zwiebel [1995] refer

[6]The model in Kaplow and Shavell (1994) builds on Becker (1964). Malik (1993) also explored the theory behind self reporting in law enforcement. See also Polinsky and Shavell (2000) for a more general discussion on the law enforcement theory in economic literature.

[7]The literature on self reporting highlights other relevant aspects of the policy in environments without corruption. See Innes (1999, 2000, 2001). For leniency programs see Motta and Polo (2003) and Buccirossi and Spagnolo (2005).

[8]See also Rose-Ackerman (1994), Hindriks, Keen, and Muthoo (1999), Livernois and McKenna (1999), and Malik (1990).

to the “respect for the law” effect.) In light of this effect, the choice of how to frame the policy might go well beyond a simple labelling or semantic issue.

Perhaps closest to our paper is Andrianova and Melissas (2008). Using a different setup, they study when governments choose to legalize an activity when officers are corrupt. They assume that once the activity is legalized, the government imposes no reduced fines or taxes, and employs no enforcement. While this might be useful in some contexts–say, when choosing zero tariffs to reduce corruption among import inspectors–their model cannot explain the role of legalization in context where harm control remains important.

2 The model

2.1 Structure

There is a measure 1 of risk-neutral citizens who cause a harm to society of $h > 0$ by committing an act that provides a private gain of x. The gain is distributed with a continuous density function $g(.)$, which is everywhere strictly positive over the support $[0, \infty)$. We assume a continuous cumulative distribution function $G(.)$ and, for simplicity, a constant hazard rate function $\frac{g(x)}{1-G(x)} = \lambda$.[9] Absent enforcement problems, a welfare maximizing government would allow only those citizens whose private benefit is $x \geq h$ to carry out the act. However, the act is not directly observable, and the government must engage in costly monitoring and enforcement. To this purpose, the government employs a measure p of officers. They are responsible for monitoring the population and reporting violators to a court of law, which in turn imposes fines. Enforcement works as follows. Each officer is randomly matched with a citizen, and the officer immediately learns whether the citizen has carried out the sanctioned activity. The officer's information is hard and verifiable in a court of law. The officer can report the violation to the judiciary system, which levies a fine f to the offender. The maximum level of sanction is $\bar{f}$, which may be interpreted as an individual's wealth.

[9] All results in the paper are generalizable to a nondecreasing hazard rate function.

2.1.1 Corruption

A corruptible officer will consider accepting a bribe b from the citizen in exchange for her silence. The size of the bribe is reached through a bargaining process. We assume that, while miscreants are willing to pay any bribe that is less than the fine, i.e. $b \leq f$, the bribe cannot be as large as the fine:

Assumption (Corruption tolerance): the maximum agreeable bribe cannot be larger than a fraction $\sigma \in (0, 1)$ of the fine.

In our model, the assumption introduces a limit to deterrence in corrupt regimes in a straightforward way. It corresponds to the reality of many bribery situations, where the bribe giver settles for a bribe that is much smaller than the full sanction. Theoretically, there are several ways to explain this condition. At its simplest, the assumption states that the larger the bribe payment demanded by an officer, the greater is the chance of detection (as in Emerson, [2006]). Bribes that are too large become either detectable to the press and scandalous to society, while a relatively small side payment would be either undetected or acceptable. Thus, our σ measures society's tolerance for corruption. Societies that are intolerant (low σ) find bribery unacceptable, and only small exchanges (that can perhaps be confused as acts of kindness rather than corruption) are possible. On the other hand, countries that are tolerant (high σ) have societies where gift exchanges (which can mask bribery) are common or consider bribe payments as a way of life.[10] In either case, a collusive agreement where bribes are too high would be uncovered by the public as blatant corruption, the officer would lose the ill-gotten wealth, and the offender would be made to pay the full fine f.[11]

[10] The prevalence of gifts exchange traditions allows individuals to mask corruption (Klitgaard, 1988), and some societies may just be more accepting when someone offers bribes to public officials (Lambsdorff, 2007).

[11] There are other possible ways to explain our assumption. Even if miscreants' ability to pay is greater or equal to the fine f, they might be unable to transfer more than a fraction σf of this wealth in bribes. This could come from the fact that the fraction $(1-\sigma)f$ is held in assets that are not easily transferrable, or whose ownership is hard to verify at the time of the bribe transfer, such as boats, landholdings, or residential units located in another location or country. While a corrupt officer might be unable to take possession of these assets, a government can reasonably be expected to find, confiscate, and sell these items. Second, the assumption is consistent with a model where part of the punishment is non-monetary in nature, wherein only a fraction σ of the punishment is extracted in monetary form and the rest administered via revenue-neutral imprisonment. Finally, the assumption would arise in a model where bribe exchanges suffer transaction

As an anti-corruption measure, the government can offer bonuses or incentives i that are paid when an officer reports an offender. Because acceptance of the bribe implies foregoing the incentive, the officer will consider only bribes that have the following characteristic: $i \leq b \leq \sigma f$. The agreement on the bribe is reached through a bargaining process, with weights to the officer of $\mu \in (0, 1)$. The equilibrium bribe is given by the following expression:

$$b(i, f) = \min \{(1 - \mu)i + \mu f, \sigma f\}, \tag{1}$$

that is, the bribe level is fully characterized by the incentive and the fine. Note that, regardless of how the bargain power is distributed between the two parties, corruption is eliminated whenever the incentive level i meets or exceeds the following no-collusion condition:

$$i \geq \sigma f \equiv i^{nc}. \tag{IC}$$

When $i < i^{nc}$, a bribe will be agreed upon, violations are not reported, and the government neither pays incentives, nor receives any income from the fine. When $i \geq i^{nc}$, no bribes are exchanged, and therefore all violations are reported, all fines are levied, and all incentives are paid.

2.1.2 Enforcement costs

Officers are risk neutral with reservation utility v, where v is strictly positive and finite. The government must offer a salary package that, in expectation, leaves officers with at least their reservation utility. Namely, the base wage w and incentive i must satisfy the following participation constraint:

$$w + \Pr(audit\ success) \max[b(i, f), i] \geq v \tag{PC}$$

costs, similar to those existing in the literature of corruption (Tirole, 1992).

where $\max[b(i, f), i]$ represents the gains obtained from either the incentive or the bribe. In addition, we assume that officers are shielded by some degree of limited liability.

Assumption (Limited liability): Officers' wages cannot fall below a certain threshold:

$$w \geq \tilde{w} \equiv 0. \tag{LL}$$

Limited liability is one way to generate a "cost of corruption"; see Burlando and Motta (2012) for an alternative modeling strategy that relies on risk aversion and that generates very similar insights. The assumption is particularly important in the context of many developing countries, where bureaucrats and law enforcement officers are generally very poorly paid, and often go unpaid. A less common occurrence is that they receive *negative* wages, although there are documented circumstances (see Besley and McClaren [1993]) in which enforcement officers essentially pay superiors for the right to enforce (and collect bribes). Even in those cases, it is likely that there is a limited liability constraint, with the minimum wage somewhere below zero. Fortunately, our paper can be easily generalized to those situations. We assume $\tilde{w} = 0$ for the sake of exposition.[12]

2.1.3 The government

We conclude the model setup by introducing a benevolent, welfare maximizing government whose contribution of enforcement expenditures B on the larger total government budget consist of wage payments net of revenues from fines. The budget process has two distortions. First, the budget is raised through distortionary taxation from the citizenship. A budget B costs society $(1 + d)B$, where d measures the size of the dead weight loss and is normalized to $d = 1$.[13] Second, the revenue generating process is subject to some bureaucracy and red

[12] Implicitly, a second limited liability assumption states that $w + max(b, i)] \geq 0$. In equilibrium, there will never be a case where bribes or incentives are negative, so the condition is never binding.

[13] This is a critical distinction between our approach of corruptible enforcement and the canonical approaches of enforcement in Kaplow and Shavell (1994) or Polinsky and Shavell (2001), where the government budget does not include the revenues from fines collected and the effect of distortionary taxation. From this perspective, our framework is similar in nature to setups more commonly found in the literature of corruption, such as in Besley and McClaren (1993) and Laffont and Tirole (1993).

tape, such that only a fraction $\alpha \leq 1$ of revenues are accounted for and can be utilized. The remaining portion of fine income is destroyed by red tape. We understand α as a measure of efficiency in a country's government.[14]

The social welfare function depends on the type of enforcement regime (clean or corrupt) and on the number of individuals who commit the sanctioned act. We denote by $\hat{x}$ the expected sanction faced under a certain enforcement regime. $\hat{x}$ is also a handy measure of effective enforcement and social harm. Welfare is

$$W(\hat{x}; i, f, w, p) = \int_{\hat{x}}^{\infty} (x - h) g(x) dx - B(\hat{x}; i, f, w, p), \tag{2}$$

where the budget function $B(\hat{x})$ will be further specialized in the next section. Note that the *enforcement regime* is characterized by the optimal selection of four policies: the number of inspectors, p; the base wage, w; the incentive pay, i; and the fine to miscreants, f.

Further assumptions and timing of the model The timing of the model works as follows. First, the government announces the full set of policies. Agents observe these policies and decide whether to engage in the harmful act. Then, officers randomly pick agents for monitoring, discover whether there was harm, and either assess the fine or agree on the bribe.

We make three additional assumptions on the parameter space, whose purpose is to keep the analysis pertinent to probabilistic enforcement by avoiding possible corner solutions where there is either perfect enforcement or no enforcement at all.

Assumption A1: $\bar{f} > \frac{h}{1+\alpha} - \frac{\sigma - \alpha}{\lambda(1+\alpha)} > 0$

Assumption A2: $\bar{f} > v/\sigma$

Assumption A3: $\bar{f} > h/\sigma$

The assumptions essentially state that the maximum fines that a government can impose are sufficiently large to be worthwhile for deterrence. Implicitly, they also state that the

[14] A modified version of costly imposition of fines is found in Polinsky and Shavell (2000).

social harm h is sufficiently large, relative to parameters. Our main results extend to the case where corner solutions are considered, but the presentation would suffer and become much more involved.

2.2 Benchmark: no corruption

We start with an economy where enforcement agents cannot collude and are always honest. It follows directly that incentives need not be offered, and wage rates remain always at the lowest level possible: $w = v$. Moreover, given that officers never accept bribes, a citizen that commits the illegal act faces an expected sanction $\hat{x} = pf$. The total quantity of crime is $1 - G(pf)$, which is also the probability of a successful audit. In total, thus, the government can expect to receive $\alpha pf[1 - G(pf)]$ in revenues from fines. With this characterization, it is straightforward to derive the welfare function. This will take into account the level of criminality, the wage bill, and revenues from fines:

$$W_{honest}(p, f) = \int_{pf}^{\infty} (x - h)g(x)dx - pv + \alpha pf[1 - G(pf)]. \tag{3}$$

It is readily observable that the optimal enforcement policy requires maximal fines $f = \bar{f}$. If fines are not maximal, the government can increase welfare by increasing the fines and reducing the amount of officers such that the enforcement level $\hat{x} = pf$ remains constant. The first and last term in equation (3) are a function of the enforcement level, and remain unchanged. However, the term in the middle is the wage bill, which is thus reduced. We lastly characterize the optimal size of the enforcement force, p^*. To determine p^*, differentiate (3) with respect to p using $f = \bar{f}$ to obtain

$$\frac{\partial W_{honest}}{\partial p} = \bar{f}(h - p\bar{f})g(p\bar{f}) - v + \alpha f[1 - G(p\bar{f})] - \alpha p\bar{f}g(pf)\bar{f}$$

This expression will be negative for $p = 0$ if v is large enough, so $p^* = 0$ is possible. Moreover, the expression can be positive for $p = 1$, so $p^* = 1$ is also possible. To keep the model as simple as possible, we always focus only on interior solutions: that is, we limit the parameter space so that the government wants *some* enforcement, and ignore those instances where it is optimal not to enforce, or to enforce every single case. Assumptions 1-3 guarantee this. An interior solution must satisfy the first-order condition that $\frac{\partial W_{honest}}{\partial p} = 0$. Making use of the fact that the hazard rate $\frac{g(\hat{x})}{1-G(\hat{x})} = \lambda$ is constant, the optimal enforcement force p^* solves

$$p^* \bar{f} \left[1 + \alpha\right] = h - \left(\frac{v}{\bar{f} g(p^* \bar{f})} - \frac{\alpha}{\lambda} \right) \tag{4}$$

The left side is the net social loss from deterring the marginal individual, who would have obtained $p^* \bar{f}$ had he committed the act and society would have obtained expected revenue from fines $p^* \bar{f} \alpha$. The left side is the net social gain from deterring the same individual, the harm avoided minus the net enforcement cost of deterring him.

While we cannot characterize the solution to this equation in a closed-form solution, it is evident that, for any given set of parameter values, the left hand side of the equation is strictly decreasing in p while the right hand side is strictly increasing in p; the solution exists and is unique.

In addition, $p_h^{*\prime} > 0$, $p_\alpha^{*\prime} > 0$ and $p_v^{*\prime} < 0$. The first derivative simply states that actions that have larger negative spillovers receive more enforcement. The second derivative implies that administrations that are more efficient at collecting fines (have higher α) have also a higher enforcement level. The implication is that enforcement is affected by a revenue concern. The final derivative shows that enforcement decreases with v, which measures the cost of an agent.

3 Enforcement in the presence of corruption

We next consider the case where corruption is possible. In solving for the optimal enforcement policy, it is useful to consider separately the case where incentives are sufficiently high so that officers do not accept bribes, and the case where incentives are low and officers are corrupt. We refer to these two situations as *corrupt* and *clean*, and we index these two regimes by

$j = c, nc$ respectively.

3.1 Clean regime

To begin, suppose that the incentive provided is $i \geq i^{nc}$. As above, officers do not accept bribes, so that enforcement is $\hat{x} = pf$ and revenues from fines are $\alpha pf[1 - G(pf)]$. On the cost side, the government pays a base wage bill pw and an incentive pay i for each fine that is levied. With these elements, the welfare function is given by

$$W_{nc}(p, w, i, f) = \int_{pf}^{\infty} (x - h)g(x)dx - pw + p(\alpha f - i)[1 - G(pf)]. \tag{5}$$

The government maximises this welfare function subject to the incentive constraint (IC), the limited liability constraint (LL) and to the participation constraint (PC) which in this case takes the form

$$w + i[1 - G(pf)] \geq v \tag{PC$_{nc}$}$$

Note that at least one or both participation and limited liability constraints must bind in equilibrium. (When they do not, the base wage w can be reduced without affecting the enforcement level, and welfare increases.) Which constraint will bind depends on the parameters of the model. Regardless of which constraint binds at the optimum, the following remark applies:

Remark 1 *The optimal policy in the clean regime includes $i = i^{nc}$ and $f = \bar{f}$. Enforcement is given by $\hat{x}_{nc} = p\bar{f}$.*

We describe the general argument for this remark here, leaving the full proof to be part of the optimal policy in proposition 2. Incentives are generally costly to the government whenever (PC$_{nc}$) is slack, and revenue-neutral otherwise. Given that increasing the incentive above i^{nc} does not serve any purpose in terms of promoting honesty, setting $i = i^{nc}$ is always an optimal response. A similar argument holds for the fine f. For any fine amount that is not maximal, it can be shown that the government can achieve the same enforcement $\hat{x} = pf$ by increasing f and reducing p, such that enforcement costs are (weakly) lower. Hence, setting the maximal fine $f = \bar{f}$ is also optimal.

The clean regime (5) is similar to the benchmark, honest case. In fact, it is readily observed that the two are identical and lead to the same welfare whenever (LL) is slack. Once (LL) binds, benchmark welfare is unattainable and corruption is socially costly. We can measure the *cost of corruption* $C_{nc}(\hat{x})$ to be the difference in welfare between the clean and the benchmark case, for any given enforcement level $\hat{x}$, using $f = \bar{f}$ and $i = i^{nc}$.[15] Formally, it is

$$C_{nc}(\hat{x}) \equiv W_{honest}(\hat{x}) - W_{nc}(\hat{x}) = \begin{cases} 0 & \text{for } v \geq \tilde{v}_\sigma \\ p\left\{\sigma\bar{f}[1 - G(\hat{x})] - v\right\} & \text{for } v < \tilde{v}_\sigma, \end{cases}$$

where $\tilde{v}_\sigma \equiv \sigma\bar{f}[1 - G(p\bar{f})]$ is the value of market wages where (LL) binds exactly. This threshold value is increasing in σ. In the top panel of figure 1 we simulate the model and plot $C_{nc}(\hat{x})$ against market wages v, for an arbitrary enforcement level, and for two values of σ. Details on the simulation and the parameters used are in Appendix C. The cost of corruption is zero for $v > \tilde{v}_\sigma$. When countries are sufficiently wealthy or have sufficiently strong institutions, the corruptibility of officers does not create distortions because the cost of paying high incentives is entirely neutralized by lowering the base salary w. When market wages are below $\tilde{v}_\sigma$, the government cannot neutralize the high incentives costs, owing to limited liability. The limited liability threshold is reached either because wages v are low, or because of high tolerance for corruption σ, which increases the equilibrium bribe and raises the incentive i^{nc} required to keep the officers clean. "Clean" enforcement becomes socially costly, with the cost increasing the poorer the country or the more tolerant to corruption the institutions are. Under plausible parameter values, our simulations suggest that the cost

[15] A comparison between the clean and the benchmark regime evaluated at their respective optimal p is discussed in the next session, when legalization is introduced. Comparing the regimes at their optimal policies does not allow us to account for the direct cost of corruption because the level of enforcement in the two regimes is allowed to vary.

of corruption can be substantial for sufficiently poor countries.

Optimal "clean" enforcement We are now left with characterizing the optimal interior $\hat{x}_{nc}$ in the clean regime. As it will be clear later in the discussion, Assumptions 1-3 prevent corner solutions, while relaxing these assumptions would not change our results. For the sake of exposition, define two market-wage threshold values $\underset{\sim}{v}_{\sigma}^{nc} \equiv \sigma \bar{f}[1 - G(\frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)})]$ and $\tilde{v}_{\sigma}^{nc} \equiv \sigma \bar{f}[1 - G(\frac{h}{1+\alpha} - \frac{\sigma-\alpha}{\lambda(1+\alpha)})]$. The following proposition characterizes the optimal policy.

Proposition 2 *The optimal interior enforcement policy with high-powered incentives includes fines and incentives as defined in remark 1 and enforcement $\hat{x}_{nc}$ as follows:*

a. *When $\bar{v} > \tilde{v}_{\sigma}^{nc}$, only* (PC$_{nc}$) *binds, the enforcement problem is equivalent to the benchmark "honest" case equation* (3)*, and $\hat{x}_{nc}$ is given by first order condition* (4)*.*

b. *When $\underset{\sim}{v}_{\sigma}^{nc} \leq \bar{v} \leq \tilde{v}_{\sigma}^{nc}$, both* (LL) *and* (PC$_{nc}$) *bind, and the enforcement level is $\hat{x}_{nc} = G^{-1}(1 - \frac{\bar{v}}{\sigma \bar{f}})$.*

c. *When $\bar{v} < \underset{\sim}{v}_{\sigma}^{nc}$,* (LL) *binds,* (PC$_{nc}$) *is slack, and the enforcement level is $\hat{x}_{nc} = \frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}$.*

Proof. See appendix. ■

When $v > \tilde{v}_{\sigma}^{nc}$ (case a.), the incentives paid out are perfectly compensated by a reduction in the base salary (i.e., the participation constraint binds), leading to zero expected rents to officers, no welfare losses from corruption, and benchmark welfare. In case b., countries with intermediate wealth ($v \in (\underset{\sim}{v}_{\sigma}^{nc}, \tilde{v}_{\sigma}^{nc}]$) optimally decrease the base wage w to the minimum level allowed by limited liability. However, officers still earn zero rent: in expected value, they obtain exactly their market wage v. The government achieves this at the cost of distorting enforcement away from the benchmark level. In fact, the distortion is such that there is *over-enforcement* with respect to the benchmark. Over-enforcement reduces the probability that an officer earns rents, and causes a reduction both in harmful activity, and in the number of times incentives are paid. This relaxes (PC_{nc}) and thus prevents the officers from earning positive corruption rents.

Avoidance of rents via over-enforcement becomes more and more costly the poorer the country. When $v \leq \underset{\sim}{v}_{\sigma}^{nc}$ (case c.), the distortion necessary is sufficiently large that it becomes optimal to pay out rents–(PC_{nc}) becomes slack. Below that threshold, optimal enforcement ceases to depend on v.

Three additional comments are in order. First, in all cases enforcement is (weakly) increasing in h, as expected: ceteribus paribus, the optimal policy involves more enforcement the more severe the act. Second, the more tolerant of corruption a country is, the higher the level of wealth $\underset{\sim}{v}_{\sigma}^{nc}$ and $\tilde{v}_{\sigma}^{nc}$ where cleaning up corruption becomes socially costly. On a more technical note, the optimal policy allows for maximal fines and binding (IC) but welfare maximization does not require this feature. Alternative policies where $f < \bar{f}$ and $i > \sigma f$ are possible, and fully spelled out in the appendix.

3.2 Corrupt regime

Consider next what happens if there are low-powered incentives, such that officers and miscreants can agree on a bribe $b(i, f)$. The potential miscreant faces an expected sanction of $\hat{x}_c = pb(i, f)$, which determines a crime level $1 - G(pb(i, f))$. Since enforcement functions through bribe exchanges, the government neither expects to pay out incentives nor receive fine income. Welfare is thus determined by the crime rate and the payment of basic salaries only,

$$W_c(p, w, i, f) = \int_{pb(i,f)}^{\infty} (x - h)g(x)dx - pw. \tag{6}$$

The government maximises this welfare function subject to $b(i, f) < i$, the limited liability constraint (LL) and the following participation constraint:

$$w + b(i, f)[1 - G(pb(i, f))] \geq \bar{v}, \tag{PC_c}$$

with either (LL) or (PC_c) or both binding at the optimum (as proven later). Incentives are never paid out, but from (6) we can immediately show that they play two roles. First, they raise the equilibrium bribe and, therefore, increase the expected sanction and consequently the compliance threshold. Second, incentives here have the same enforcement function as fines f in a standard beckerian enforcement setting. The following result should, therefore, be quite unsurprising:

Remark 3 *The optimal enforcement policy in the corrupt regime includes a policy with low powered incentives $i < i^{nc}$ such that $b = \sigma f$ and $f = \bar{f}$ (fines and bribes are maximal). Thus, $\hat{x}_c = \sigma p \bar{f}$.*

The full enforcement policy will be characterized and proved later. Suffice here to offer a few observations. Note that deterrence from corrupt officers is lower than deterrence from non-corruptible ones: for a given number of police officers p, $\hat{x}_c = \sigma p \bar{f} < \hat{x}_{nc} = p\bar{f}$. This is a clearly negative aspect of corruption-based enforcement. However, there are two countervailing factors that make corruption more desirable. First, bribes can reduce the size of the budget by reducing wages that are paid by the government. Importantly, the higher the σ, the lower the base wage w that needs to be offered to officers. Secondly, an enforcement system based on bribes avoids deadweight losses associated with the collection of fines. The lower α is, the larger these deadweight losses are and, as a consequence, the larger is the advantage of corruption.

To see how these different elements play against one another, define the cost of corruption $C_c(\hat{x})$ to be the difference in the maximum welfare between the corrupt and the benchmark case, for enforcement level $\sigma p \bar{f} = \hat{x}$, subject to the constraints (LL) and (PC_c):

$$C_c(\hat{x}) \equiv W_{honest}(\hat{x}) - W_c(\hat{x}) = \begin{cases} (1-\sigma)pv - (1-\alpha)\sigma p \bar{f}[1-G(\hat{x})] & \text{for } v \geq \tilde{v}'_\sigma \\ \sigma p \left\{ \alpha \bar{f}[1-G(\hat{x})] - v \right\} & \text{for } v < \tilde{v}'_\sigma, \end{cases}$$

where $\tilde{v}'_\sigma \equiv \sigma \bar{f}[1 - G(\sigma p \bar{f})]$ is increasing in σ, as for the case of the clean regime.

We plot the $C_c(\hat{x})$ function in the bottom panel of figure 1 for two values of σ. $C_c(\hat{x})$ can be either positive or negative, depending on the value of σ and v. A corrupt system has lower deterrence and this hurts welfare when a country is rich ($v \geq \tilde{v}'_\sigma$): owing to the reduction in deterrence, the government needs to hire (and pay) many more officers to achieve the desired level of enforcement. Clearly, this increases the cost of enforcement relative to the benchmark, especially when tolerance for corruption σ is low, and bribes are not effective deterring tools. As market wages fall, the cost of corruption falls, and we obtain the familiar observation that, in many instances, an enforcement system based on bribes is efficient and superior to whatever is achievable by an honest regime. A corrupt regime simply pays its own officers less, in exchange for allowing them to keep their bribes.

Once market wages fall even further below $\tilde{v}'_\sigma$, additional reductions in v increase the cost of corruption. This is because at low market wages enforcement is no longer affected by reduction in v, whereas honest enforcement continues to become cheaper and cheaper. Meanwhile, all the potential revenues accrued in the honest regime are essentially passed to enforcement agents in the corrupt regime. Thus, corruption as an institution is most advantageous when the country has middle income, but is less advantageous or even disadvantageous for the same country at a higher and at a lower poverty level.

Optimal "corrupt" enforcement Define two threshold wage levels $\underset{\sim}{v}^c_\sigma \equiv \sigma \bar{f}[1 - G(h)]$ and $\tilde{v}^c_\sigma \equiv \sigma \bar{f}[1 - G(\frac{h}{2})]$. As before, Assumptions 1-3 prevent corner solutions, while relaxing these assumptions would not change our results. The following proposition characterizes the optimal policy under corruption.

Proposition 4 *The optimal interior enforcement policy under low-powered incentives is as follows:*

a. *When* $v > \tilde{v}^c_\sigma$*,* (LL) *is slack and* (PC$_c$) *binds, and the interior optimal enforcement policy* $\hat{x}_c$ *solves* $\hat{x}_c = \frac{1}{2}[h + \frac{1}{\lambda} - \frac{v}{\sigma \bar{f} g(\hat{x}_c)}]$.

b. *When* $\underset{\sim}{v}^c_\sigma \leq v \leq \tilde{v}^c_\sigma$*,* (LL) *and* (PC$_c$) *both bind with equality, and the enforcement level is*

$\hat{x}_c = G^{-1}(1 - \frac{v}{\sigma f})$.

c. *When* $v < \underset{\sim}{v}^c_\sigma$*,* (LL) *binds,* (PC$_c$) *is slack, and the optimal level of enforcement is* $\hat{x}_c = h$*.*

Proof. See appendix. ■

When $v > \tilde{v}^c_\sigma$ (case a.), the government is able to reduce wages below the market level, such that gains from bribes are exactly offset by the lower base pay. Officers do not earn rents. As market wages fall further below the threshold $\tilde{v}_c$ (case b.), the government cannot reduce wages further, but can still limit the expected gains of officers by hiring more officers, which reduces the number of miscreants, and thus reduces the probability of a bribe exchange. Thus, officers continue to earn no surplus from bribe taking. As market wages fall below $v = \underset{\sim}{v}_c$, enforcement reaches a maximum $\hat{x} = h$. At this level, the government is unwilling to increase enforcement further, so any further reduction in market wages translate into positive rents to officials.

Two additional observations are in order. First, it is tempting to think that the maximum amount of enforcement under the corrupt regime, $\hat{x} = h$, is the "optimal" amount of enforcement. But this observation would only be correct in a frictionless world.[16] Second, it is not possible to derive any consistent result about the amount of over-or under-enforcement in the corrupt regime, relative to the benchmark case; the comparison is very sensitive to differences in σ and α.

As in the clean regime, it is possible to have multiple optimal policies, some of which do not require maximal fines or maximal bribes. However, all these policies are qualitatively equivalent to one presented in our proposition. It is without loss of generality that we specialize to the case where fines and bribes are maximal, but the proof includes all others

[16] In a frictionless world where there are no inefficiencies from transferring resources though a government budget B, the only concern for the government is the reduction of the social harm. An enforcement of $\hat{x} = h$ guarantees that only those whose private benefit x exceed the social harm h decide to engage in the harmful activity. However, the world we model is not frictionless. Our government has a *revenue concern*, where revenues are useful to reduce deadweight losses originating from other government expenditures in the larger government budget.

for completeness.

3.3 Optimal regime choice in the absence of legalization

The government can move from a corrupt to a clean regime by modifying the incentive pay i so as to meet or violate the no-corruption compatibility constraint (IC). The final outcome is determined by maximizing both W_{nc} and W_c, and then choosing whichever is larger. When choosing which regime to adopt, the government essentially trades off lower wages in a corrupt regime, with the revenue that is collected when the regime is clean and the higher per-officer deterrence. Ceteribus paribus, a high-σ country will be more likely to choose corruption while a low-σ country will be more likely to prevent corruption. Armed with this intuition, we first define the level σ such that the government is indifferent between the two regimes, and then prove that, for any parameter value, low σ (i.e., below the threshold) involve no corruption, and high σ (above the threshold) involve corruption. We then describe how this threshold changes across parameter values.

Definition 5 *Let σ^* be the level of σ such that, for given parameter values $h, v, \bar{f}, \alpha$, the optimal policies in both regimes are such that $W_{nc}^* = W_c^*$.*

Proposition 6 *For all parameter values with interior enforcement level:*

i. *There exists a unique σ^* such that when $\sigma \leq \sigma^*$ the regime is clean (policy follows proposition 2), and when $\sigma > \sigma^*$ the regime is corrupt (policy follows proposition 4).*

ii. *$\sigma^* \geq \alpha$, with equality iff $v \leq \alpha \bar{f} \left[1 - G(\frac{h}{1+\alpha})\right]$.*

We sketch the intuition here and address the reader to the appendix for the complete proof. In the first part, we establish in a lemma that when $\sigma < \alpha$, the regime is always clean ($W_{nc}^* > W_c^*$), and when $\sigma = 1$ the regime is always corrupt ($W_{nc}^* < W_c^*$). Second, we show that W_{nc}^* is continuous and nonicreasing in σ, and that W_c^* is continuous and nondecreasing in σ. Those facts establish the existence of σ^*: the two welfare functions need to cross at some intermediate σ^*. To demonstrate uniqueness, we show that $\frac{\partial W_c^*}{\partial \sigma} \geq 0$ and $\frac{\partial W_{nc}^*}{\partial \sigma} \leq 0$; moreover, whenever the j-regime welfare W_j^* does not vary with σ (i.e., $\frac{\partial W_j^*}{\partial \sigma} = 0$), the other is strictly increasing or decreasing with σ. For part (ii.), we look specifically at an economy where $\sigma = \alpha$, and show that when $v \leq \tilde{v}_\sigma^{nc}$, $W_c^* = W_{nc}^*$, and when $v > \tilde{v}_\sigma^{nc}$, $W_c^* < W_{nc}^*$.

The proposition is best understood by looking at figure 2, which plots the optimized welfare functions in both regimes on the (σ, v) planes (details on the simulation in the appendix B). Welfare is negatively related to v in both regimes, a consequence of the fact that increases in v increase the budget devoted to enforcement. As expected, welfare in the clean regime is negatively associated with σ, but only at low levels of income v, whereas welfare in the corrupt regime is positively associated with σ at high levels of v. It is especially clear that welfare is very sensitive to changes in σ for the corrupt regime, because in this regime σ directly affects deterrence. σ^* is defined by the intersection of the two planes.

Figure 3 more clearly traces σ^* for two different levels of h, i.e., for activities of different severity. For low levels of v, we have that $\sigma^* = \alpha$. Note that this condition implies that corruption is preferred for all cases where $i^{nc} = \sigma f > \alpha f$, where enforcement incentive costs are larger than revenues. The only cases where officers will remain clean are in cases where $\sigma < \alpha$, that is, where revenues from enforcement outweigh incentive costs. Thus, revenue-rich enforcement activities like tax audits should always remain clean, whereas arguably "low revenue" activities like pollution control would remain corrupt. Note that, as v increases, σ^* also begins to increase above α, and the clean regime becomes preferable for a wider set of parameters. The point where this happens is when $v = \alpha \bar{f}[1 - G(\frac{h}{1+\alpha})]$, which correspond to the market wage where the limited liability condition (LL) ceases to be binding in the clean regime. Above this market wage, the clean regime becomes generally more preferable because the government does not need to introduce any distortions to manage officers' corruptibility. In addition, as each officer becomes more expensive, the government values more the higher deterrence level achieved in a clean regime.

Note that the σ^* also responds to the severity of the misdeed: increasing h pushes the σ^* threshold to the left, such that officers are less likely to be corrupt for more severe crimes. This is because, when the severity of the crime increases, the optimal response in both clean and corrupt regime is to increase the amount of enforcement. With higher enforcement comes a lower level of harmful behavior. This reduces social harm on the one hand, and also reduces the share of total officers' pay derived from incentives or bribes. In turn, this slackens the (LL) constraints for all regimes, such that $\underset{\sim}{v}^j_\sigma$ and $\tilde{v}^j_\sigma$ shift to the left.

Proposition 6 and figure 3 thus suggests what is well known in the literature: the corrupt regime is more likely to be preferable in poor countries, where governments face anti-corruption policies that are too expensive to implement. However, recall that, at low levels of v, both corrupt and clean regime perform badly against the benchmark regime. Thus, the fact that at low v enforcement agents are corrupt is less a sign of efficiency, and more of a choice between two bad options.

4 Tax and Legalize

We now introduce the tax-and-legalize mechanism. The government now makes the harmful activity legal, but requires the payment of a reduced fine or tax r. It now employs a police force to monitor the payment of the tax and assess fines f as the punishment for tax evasion.

The timing of the model is modified as follows: the government chooses an enforcement policy f, p, w, r. Individuals then simultaneously choose whether to commit the harmful act and, if so, whether to pay the tax r. Audits follow as usual, except that the officer now must only determine whether an act has been committed without the tax payment. If there was tax avoidance, the officer can assess the fine f or accept a bribe b.

It is reasonable to assume that the bureaucratic process for processing taxes would follow a different path than a sanctioned fine. A citizen who is reported to the judiciary by a law enforcer has the right to defend himself in a court of law, and demonstrating his culpability is time consuming and expensive. The same cannot be said for processing a taxpayer. As a consequence, the bureaucratic procedure needed to process the tax is more efficient and less expensive. We again abstract from this point already highlighted by Kaplow and Shavell (1994) to pinpoint a different mechanism that is not dependent on a different bureaucratic efficiency of self reporting. We thus assume that the tax r is subject to the same efficiency losses as other fines, and the government retains only αr of the paid tax.

In a legalized regime, an individual who commits a harmful act can either pay the tax r, or avoid the tax and risk being caught - whichever is more convenient (less expensive) in expectation to him. The punishment f_j is equal to f in the clean regime ($j = nc$) or the bribe b in the corrupt regime ($j = c$). An individual with private gain x may commit the act if his private benefit from the act exceeds the cost:

$$x_j \geq \min[r, pf_j] \equiv \hat{x}_j^l,$$

where r is now part of the set of policy instruments available to the government. To get the optimal level of r, consider first the case $r > pf_j$. Because the tax is more expensive than the expected full sanction, perpetrators avoid the tax. In this case, the tax is ineffective, and no one employs it.

Now suppose $r \leq pf_j$. Clearly, everyone pays the tax. Since $\hat{x}_j^l = r$, the total number of crimes committed is $1 - G(r)$. Since officers never find a tax evader, they never earn bribes or incentives, and their only source of income (and only source of enforcement cost) is the base wage w. Thus, the welfare achieved is

$$W_l^j(r, p, w, i, f) = \int_r^{\infty} (x - h)g(x)dx - pw + \alpha r[1 - G(r)], \tag{7}$$

subject to the usual constraints (PC) and (LL).

Proposition 7 explains the optimal tax-and-legalize policy.

Proposition 7 *When the tax-and-legalize policy is adopted, all perpetrators pay the tax and:*

(i) $i \geq \sigma f$ (officers are always honest);

(ii) $r = pf$ *(the tax is equal to the expected punishment);*

(iii) $w = v$ *(officers' base wage is equal to their reservation wage).*

Proof. *see the Appendix.* ■

In equilibrium, incentives are sufficiently high to ensure that officers are honest, but are never paid out because every perpetrator chooses to pay the tax. Even though officers never uncover evaders, the presence of officers and the incentives they could receive do have a role: they act as a credible threat against tax evasion, and guarantee the officers' honesty when offered bribes. This mechanism resembles the 'threat' found in modern income tax systems, or the enforcement of parking regulations: cities allow drivers to park in certain areas only if they pay a tax at the curb by feeding a meter. People feed the meter in the off chance that a parking inspector passes by and fines those who did not.

With this proposition, maximized welfare is a function of fines and enforcement costs,

$$W_l(pf) = \int_{pf}^{\infty} (x - h)g(x)dx - pv + p\alpha f[1 - G(pf)]. \tag{8}$$

It is readily observed that this is the same welfare function achieved when officers are honest, $W_{honest}(pf)$, equation (3). This implies that fines are maximal at $\bar{f}$ and the optimal size of the office corp is the same under the tax-and-legalize regime as in the benchmark case, that is, dictated by the first order conditions (4). We highlight this in the following remark:

Remark 8 *The tax-and-legalize regime achieves the benchmark policy and welfare.*

4.1 Optimal regime choice with legalization

Having determined that the tax-and-legalize regime achieves the same welfare as the benchmark regime, we can use the results from section 3.1 to readily compare a regime cum legalization with a clean regime without it. First, legalization does not improve welfare if a country is sufficiently rich such that (LL) is slack (i.e., for $v > \tilde{v}_{\sigma}^{nc}$). At lower levels of wealth

($v \leq \tilde{v}_\sigma^{nc}$), welfare in the clean regime is limited by the additional (LL) constraint, which is absent in the tax-and-legalize regime. Legalization thus offers strictly higher welfare.

Having established that the tax-and-legalize regime replaces the clean regime at low levels of wealth, the following proposition shows the condition under which the tax-and-legalize regime *also* replaces the corrupt regime:

Proposition 9 *Legalization reduces the parameter region where corruption is optimal iff the country is sufficiently poor ($v < \tilde{v}_\sigma^{nc}$). In addition, it always replaces corruption when the country is very poor ($v \leq \alpha \bar{f}[1 - G(h)]$), regardless of how corruption tolerant the country is.*

Proof. See appendix. ■

Figures 4, 5 and 6 illustrate the welfare and the various regime choices with and without legalization. Figure 4 plots the welfare levels for each of the three regimes on the (v, σ) axis. The blue lines in figures 5 and 6 plot the σ^* that divides the clean and the corrupt regime, while the green line identifies the "new" σ^* with legalization. It is clear that legalization is implemented both in previously clean and corrupt regimes. However, the parameter space taken by the tax-and-legalize regime is more likely to include previously corrupted regimes when α is relatively small. Thus, this policy is more important for poor, inefficient and corrupt countries.

A final point that is relevant is that the size of the region taken up by the tax-and-legalize regime falls the larger the social cost h: legalization should be more commonly used to regulate activities that are not too damaging.

4.2 Social harm under legalization

We have seen that legalization improves social welfare in those parameter regions where corruption is most costly–at low levels of wealth. How does legalization affect enforcement levels and, consequently, the amount of social harm suffered? In the previous sections we established that the benchmark regime (which is the legalized regime) might feature lower enforcement than both the clean and corrupt regime. This is important because a common concern with legalization is that it may increase the amount of harmful activity. In what follows, we consider in turn the optimal amount of enforcement under legalization relative to $\hat{x}_{nc}$ and $\hat{x}_c$, and will generally find that, in most areas where one expects to find legalization, more harm indeed must be allowed.

Harm relative to the clean regime: As discussed in section 3.1, optimal enforcement under legalization has generally higher levels of socially harmful activity when measured against the clean regime. More formally:

Remark 10 *Relative to optimal enforcement in the clean regime, legalization leads to lower enforcement for wealth values $(1-\lambda h)\gamma_{\sigma}^{nc} < v < \tilde{v}_{\sigma}^{nc}$, and higher enforcement for wealth values $v < (1-\lambda h)\gamma_{\sigma}^{nc}$, where $\gamma_{\sigma}^{nc} = \underset{\sim}{v}_{\sigma}^{nc}/(1+\alpha-\sigma)$. When the social harm is sufficiently serious ($h > 1/\lambda$), it is always the case that legalization leads to an increase in the amount of the harmful act.*

The proof is relegated in Appendix B (not for publication.) This is a striking result: in most cases, whenever it is socially beneficial to switch from a clean regime without legalization to a tax-and-legalize regime, the amount of harm allowed increases. This is driven by the fact that, when $v < \tilde{v}_{\sigma}^{nc}$, the optimal response in the clean regime is to over enforce, and that over-enforcement is corrected by legalization. In particular, as v declines below $\tilde{v}_{\sigma}^{nc}$, over-enforcement increases, reaches its maximum at $v = \underset{\sim}{v}_{\sigma}^{nc}$, and then shrinks again because the enforcement level in the clean regime $\hat{x}_{nc}$ remains constant while the enforcement level in the tax-and-legalize regime keeps increasing as v decreases. At the wealth level $v = (1-\lambda h)\gamma_{\sigma}^{nc}$, we have that the enforcement level are identical. While legalization leads to enhanced enforcement when market wages are below this threshold, it should be noted that the threshold is negative (and therefore never reached) when $\lambda h > 1$, that is, when the harm from the sanctioned activity is sufficiently serious. Thus, the parameter space where under-enforcement happens can be limited.

Harm relative to the corrupt regime: The discussion of enforcement under legalization relative to the corrupt regime is not as clear cut: depending on parameter values, self reporting could have higher or lower levels of enforcement, so the amount of the sanctioned activity might be higher or lower. We thus focus our attention to the parameter space where legalization most clearly allows a switch of regime from corrupt to clean, i.e., when $v < \alpha\bar{f}[1 - G(h)]$ as discussed in Proposition 9.

Remark 11 *When $v < \alpha\bar{f}[1 - G(h)]$, self reporting has lower enforcement levels than the corrupt regimes for wealth values $v > (1 - \lambda h)\gamma^c_\sigma$ and higher enforcement for wealth values $v < (1 - \lambda h)\gamma^c_\sigma$, where $\gamma^c_\sigma = \underset{\sim}{v}^c_\sigma \alpha/\sigma$. When the social harm is sufficiently serious ($h > 1/\lambda$), there is more harm under self reporting.*

The proof is relegated in Appendix B (not for publication.) The remark suggests that, in many relevant cases where you expect a switch from corruption to a clean regime with legalization, the shift causes the amount of harm to increase. As in the case for the clean regime, this is due to the fact that there is over-enforcement in the corrupt regime, which is corrected by legalization. The remark also identifies the condition on wealth below which legalization has more enforcement. As for the clean regime case, this condition $v < (1-\lambda h)\gamma^c_\sigma$ is never met when the harm is sufficiently large ($\lambda h > 1$). If the activity is very harmful $h > \frac{1}{\lambda}$, legalization always increases the amount of harm.

Unfortunately, we cannot derive any additional conclusion on enforcement levels for values of larger values of wealth (i.e., $v > \underset{\sim}{v}^c_\sigma$) where there might also be switches from a corrupt regime to the legalized regime. To provide some intuition of what happens there, we simulate the model and draw the the optimal $\hat{x}_j$ on the (v, σ) plane for a high-harm activity ($h > 1/\lambda$) in figure 7 and 8. The figures compare enforcement in the clean and corrupt case against the legalized regime. It is quite clear that enforcement is substantially lower under legalization in the parameter regions where legalization is socially optimal. In addition, the area where the corrupt regime has a higher enforcement level than the legalized regime is significantly larger than the area identified in remark 11. On the other hand, in figures 9 and 10, we show that for a low-harm activity ($h < 1/\lambda$) there is a region where, as expected, self reporting has higher enforcement levels.

In conclusion, our model shows that legalization will generally increase harm, but that this increase is *optimal* for society. But even in our framework it is not hard to see that this aspect might be problematic. In a world where utility is not perfectly transferable, the harm suffered from certain individuals might not be fully refundable. Legalization could easily spiral into a controversial and politically unpalatable choice. This might explain why legalization is not adopted in the real world as frequently as our model suggest.

It is important to stress that the decrease in enforcement brought by legalization is due to the changes in the incentive costs faced by the government, and it has nothing to do with either changes in consumer taste or to introduction of a revenue concern for the government brought by legalization. This is because in our model legalization does not change the demand for the illegal good, and the government always faces a revenue concern–even in the absence of legalization.[17]

5 Conclusion

In this paper, we studied the effects of corruption on law enforcement policies and showed that these effects vary with the country's wealth, tolerance for corruption, and bureaucratic inefficiency. In our model, law enforcers not only punish miscreants who are caught, but also act as a deterrent against committing the harmful act to begin with. The main drawback of corruption is that it dilutes deterrence, by deducting the cost associated with committing a sanctioned act. As in much of the economic literature on corruption, however, we find that the practice is indeed preferable in many cases: cleansing enforcement officials of corruption can be expensive, and the alternative–an honest but inefficient bureaucracy–may not be very desirable. In particular, the poorer the country, the less likely it is going to be that a

[17]There is significant empirical evidence that legalization (or, conversely, prohibition) of an illegal activity changes the demand for a good. See footnote 1. In our model, we could easily introduce this feature by having a measure of infinitely risk averse citizens. Self reporting would immediately result in a demand-side response, with higher demand for the harmful good at all levels of enforcement. Notes available upon request.

government will adopt sufficiently stringent anti-corruption policies needed to keep officers honest. While corruption is indeed socially preferable at low income levels, it is also at those levels that the practice is at its most costly. We highlight this by showing high welfare differentials against equivalent countries with same level of structural parameters but an inability for officers to receive bribes. At intermediate income levels, corruption may be efficient: it provides the right combination of deterrence, low enforcement costs, and lack of bureaucracy. At higher income levels, corruption ceases to be either a resource or a problem.

In this rich but simple model of corruption, we find that a policy of legalization changes the incentives faced by the policy makers in such a way that it reduces the situations in which corruption arises and eliminates the costs associated with the threat of corruption. More importantly, legalization is *always* preferable at the lowest income levels–when corruption is most likely to occur and where corruption incurs the highest costs.

This stark result from the model raises an important question: Why is legalization/self reporting not more widespread in poor countries? Possibly because legalization achieves this higher welfare by increasing the amount of socially harmful activities. In a political economy setting where a policy is chosen not only on its impact on welfare, but also on the political viability of the policy, legalization could very well be controversial. For instance, if citizens are more likely to observe (and vote on) the amount of social harm as opposed to the amount of taxation, legalization would be a politically unpalatable choice. Alternatively, if the impact of the harmful activity is non-uniform, the emergence of interest groups becomes plausible.

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6 Appendix

6.1 Proof of proposition 2

We first prove statements a. and c., and then use the results to prove statement b. The proofs demonstrate that the optimal set includes a maximal f and $i = i^{nc}$. See web Appendix B for a proof with a characterization of all optimal policies (including those where $f < \bar{f}$, and $i > i^{nc}$).

Part a. Consider first the case where (LL) is slack. Then, (PC_{nc}) binds and, from (PC_{nc}), we get that the optimal wage is $w_{nc} = v - i[1 - G(pf)]$. Replacing this in the welfare function (5), we get that

$$W_{nc}(p, f) = \int_{pf}^{\infty} (x - h)g(x)dx - pv + p\alpha f[1 - G(pf)]. \tag{9}$$

Note first that welfare does not depend on i, and any $i \geq \sigma f$ satisfies (IC). In addition, the welfare is equivalent to (3), the benchmark case without the possibility of corruption. The optimal policy thus follows the benchmark case, which means that f is maximal and the optimal interior solution p_{nc} is determined by the first order condition (4).

We next determine the optimal i^*. As long as $v > i^*[1 - G(p_{nc}\bar{f})]$, (LL) is slack. Thus, any $i^* \in [\sigma\bar{f}, \frac{v}{1-G(p_{nc}\bar{f})}]$ ensures that (LL) does not bind. Next, we show the parameter space where this solution is feasible. The largest v such that (LL) binds is $v = i^*[1 - G(p_{nc}\bar{f})]$; substituting this in (4) we get

$$h - (1 + \alpha)p_{nc}\bar{f} = \frac{i^*[1 - G(p_{nc}\bar{f})]}{\bar{f}g(p_{nc}\bar{f})} - \frac{\alpha}{\lambda}. \tag{10}$$

Solving for $p_{nc}\bar{f}$ and considering that the hazard rate $\frac{[1-G(p_{nc}\bar{f})]}{g(p_{nc})} = \frac{1}{\lambda}$, we get $p_{nc}\bar{f} = \frac{h}{1+\alpha} - \frac{i^*-\bar{f}\alpha}{\bar{f}\lambda(1+\alpha)}$. Substituting $p_{nc}\bar{f}$ and $i^* = \sigma\bar{f}$ into the participation constraint, we find that this solution is feasible for $v > \tilde{v}_{\sigma}^{nc} \equiv \sigma\bar{f}\left[1 - G\left(\frac{h}{1+\alpha} - \frac{\sigma-\alpha}{\lambda(1+\alpha)}\right)\right]$.

It remains to be demonstrated that, in the parameter space where the solution is feasible, it is also optimal. This follows immediately from the fact that when $v > \tilde{v}_{\sigma}^{nc}$, the government achieves benchmark welfare, and the benchmark welfare is strictly better than any clean regime welfare where (LL) binds. Thus, it is never optimal to set $i > \sigma\bar{f}$ in such a way that (LL) binds. Moreover Assumptions 1-3 ensure no corner solutions.[18]

Part c. Next consider the case where (LL) binds and (PC_{nc}) does not. Substituting $w_{nc} = 0$ in the welfare function (5), we get an equation that is decreasing in i. Thus, i should be reduced until (IC) binds: $i^{nc} = \sigma f$. The welfare function takes the form

$$W_{nc}(p, f) = \int_{pf}^{\infty} (x - h)g(x)dx + pf(\alpha - \sigma)[1 - G(pf)]. \tag{11}$$

This function does not separately identify p from f: rather, it identifies $\hat{x}_{nc}$, and then any combination p and f such that $pf = \hat{x}_{nc}$ is equally acceptable. Here, we focus on $f = \bar{f}$. See web appendix for a proof with a characterization of all optimal policies. Setting the derivative of W_{nc} with respect to p equal to zero we get

[18] An interior solution is guaranteed if $v < \bar{f}(h\lambda + \alpha)$ (always satisfied by assumption A2 and by assumption A1, which implies that $h > (\sigma - \alpha)/\lambda$ and if $v > \bar{f}g(\bar{f})\left(h - \bar{f}[1 + \alpha] + \frac{\alpha}{\lambda}\right) = \lambda[h - (1+\alpha)\bar{f} + \alpha/\lambda]\bar{f}[1 - G(\bar{f})]$, which is always satisfied because the threshold is smaller than $\tilde{v}_{\sigma}^{nc}$ and by assumption A1.

$$[h-(1+\alpha-\sigma)p_{nc}\bar{f}]g(p_{nc}\bar{f})=(\alpha-\sigma)[1-G(p_{nc}\bar{f})]; \tag{12}$$

Dividing both sides by $g(p_{nc}\bar{f})$ and substituting $\frac{1-G(p_{nc}\bar{f})}{g(p_{nc}\bar{f})}=\frac{1}{\lambda}$, and then solving for p_{nc}, we obtain that $p_{nc}\bar{f}=\hat{x}_{nc}=\frac{h}{1+\alpha-\sigma}-\frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}$. An interior solution for p is guaranteed by assumption A1 and by $h>\frac{\sigma-\alpha}{\lambda}$, which is again satisfied when A1 is satisfied. Thus, $f=\bar{f}$ is feasible and guarantees an interior solution.

Finally, this solution applies whenever (PC$_{nc}$) is slack; that means that it is feasible in the space $v<\sigma\bar{f}\left[1-G\left(\frac{h}{1+\alpha-\sigma}-\frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}\right)\right]$.

Part b. Next consider the case where (PC$_{nc}$) and (LL) bind at the same time. Substituting $w_{nc}=0$ and the binding (PC$_{nc}$) in the welfare function (5), we get an equation that is decreasing in i. Thus, $i^{nc}=\sigma f$, the welfare function takes the form (11), and the optimal enforcement policy p_{nc} and f_{nc} solves $v=\sigma f_{nc}[1-G(p_{nc}f_{nc})]$. Rearranging, we get the optimal interior enforcement solution $\hat{x}_{nc}=G^{-1}(1-\frac{v}{\sigma f_{nc}})$. Plugging this into (11), we get that the equilibrium welfare is

$$W_{nc}(p_{nc},f_{nc})=\int_{\hat{x}_{nc}}^{\infty}(x-h)g(x)dx+p_{nc}(\alpha-\sigma)\frac{v}{\sigma}. \tag{13}$$

We next show that, if $\underset{\sim}{v}_{\sigma}^{nc}\leq v\leq\tilde{v}_{\sigma}^{nc}$, $f_{nc}=\bar{f}$. Suppose $f<\bar{f}$, but p is chosen such that $v=\sigma f[1-G(pf)]$. Then, we could increase f to $f'>f$ and reduce p to $p'<p$ such that $f'p'=pf$. Note that $v<\sigma f'[1-G(p'f')]$, (PC$_{nc}$) is now slack, and the welfare achieved is determined by equation (11). Comparing this welfare function with equation (13), the two are identical:

$$\begin{aligned}W_{nc}(p,f)-W'_{nc}(p',f')&=p(\alpha-\sigma)\frac{v}{\sigma}-p'f'(\alpha-\sigma)[1-G(p'f')]\\&=(\alpha-\sigma)\{pf[1-G(pf)]-p'f'[1-G(p'f')]\}=0.\end{aligned}$$

However, unlike $W_{nc}(p,f)$, $W_{nc}(p',f')$ is generally not evaluated at its optimal expected sanction. The optimal expected sanction $\hat{x}_{nc}=p'f'$ is $p'f'=\frac{h}{1+\alpha-\sigma}-\frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}$ (see Part c. of this proof). The only time when $pf=p'f'$ and the two welfare functions are equal is when $v=\sigma f\left[1-G\left(\frac{h}{1+\alpha-\sigma}-\frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}\right)\right]<\underset{\sim}{v}_{\sigma}^{nc}$. But here we are considering the case where $v\geq\underset{\sim}{v}_{\sigma}^{nc}$. So it must be that the welfare is higher with f'. This contradicts the assertion that f was optimal.[19]

We conclude by noting that this solution is feasible for the space $\underset{\sim}{v}_{\sigma}^{nc}\leq v\leq\tilde{v}_{\sigma}^{nc}$. It can be verified that at the boundary $v=\underset{\sim}{v}_{\sigma}^{nc}$, the solution is $p_{nc}\bar{f}=\hat{x}_{nc}=\frac{h}{1+\alpha-\sigma}-\frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}$, which is the same solution found in Part c. Also, at the boundary $v=\tilde{v}_{\sigma}^{nc}$, the solution is $p_{nc}\bar{f}=\hat{x}_{nc}=\frac{h}{1+\alpha}-\frac{\sigma-\alpha}{\lambda(1+\alpha)}$, which is the solution for Part a. Outside of this interval, the solution in Part b. is dominated by the solutions in Part c. and Part a. Thus, the solution in Part b. applies to the space $\underset{\sim}{v}_{\sigma}^{nc}\leq v\leq\tilde{v}_{\sigma}^{nc}$, and W_{nc}^{*} is continuous in v.

6.2 Proof of proposition 4

Here we prove that in the corrupt regime maximal b and f (i.e., $b=\sigma\bar{f}$ and $f=\bar{f}$) are always in the optimal policy set, and analyze this solution only. The complete proof that solves for all possible policies can be found in the web Appendix B.

[19] An interior solution requires $v>\sigma\bar{f}[1-G(\bar{f})]$, which is satisfied by $v>\underset{\sim}{v}_{\sigma}^{nc}$ and by assumption A1, and $v<\sigma\bar{f}$ (assumption A2).

Part a. Consider first the case where, for a given value of p, b and w, a corrupt regime has $b < \sigma f$, and (LL) does not bind. First, note that the participation constraint must be biding with equality. Otherwise, the government can reduce w without changing either b or p, and the wage bill is reduced in a way that does not impact the amount of harm. Thus, $w_c = v - b(i,f)[1 - G(pb(i,f))]$. Next, a small increase in i induces the equilibrium bribe b to increase to $\tilde{b}$ according to (1), and the participation constraint (PC_c) slackens. The government can then choose to hire fewer officers $\tilde{p}$ such that $\tilde{p}\tilde{b} = pb$, and keep the pay w. With fewer officers, the wage bill is reduced without affecting the level of harm. Thus, for any wage w that satisfies (PC_c), i is set to a value such that bribes are maximal: $b = \sigma f$.[20] Since fines also increase the size of the bribe, by the same argument the fines are also maximal: $f = \bar{f}$. Substituting this into the welfare function (6), we get

$$W_c(p) = \int_{\sigma p \bar{f}}^{\infty} (x - h) g(x) dx - pv + \sigma p \bar{f}[1 - G(\sigma p \bar{f})]. \tag{14}$$

To find the optimal force size p_c, take the derivative of the welfare function with respect to p:

$$\frac{\partial W_c}{\partial p} = (h - \sigma p_c \bar{f}) g(\sigma p_c \bar{f}) \sigma \bar{f} - \bar{v} - \sigma p_c \bar{f} g(\sigma p_c \bar{f}) \sigma \bar{f} + \sigma \bar{f}[1 - G(\sigma p_c \bar{f})] \tag{15}$$

An interior solution must satisfy the first-order condition that $\frac{\partial W_c}{\partial p} = 0$. After rearranging and using the fact that $\frac{1 - G(\sigma p_c \bar{f})}{g(\sigma p_c \bar{f})} = \frac{1}{\lambda}$, the optimal interior solution p_c solves $p_c \bar{f} = \frac{1}{2\sigma}[h + \frac{1}{\lambda} - \frac{v}{\sigma \bar{f} g(\sigma p_c \bar{f})}]$. This is an implicit function; since the left hand side is increasing in p while the right hand side is decreasing in p, the solution is unique and it exists. Finally, we determine the parameter space such that the limited liability does not bind. (LL) is slack if $v > \sigma \bar{f}[1 - G(\sigma p_c \bar{f})]$. Substituting this in (15) and rearranging, we get the threshold level of enforcement, $\sigma p_c \bar{f} = \frac{h}{2}$. Hence, for any $v > \tilde{v}_{\sigma}^{c} \equiv \sigma \bar{f}[1 - G(\frac{h}{2})]$, (LL) is slack, ($\text{PC}_c$) binds and the solution discussed in this part of the proof applies.[21]

Part c. Next consider the case where (LL) binds and (PC_c) does not. Substituting $w_c = 0$ in the welfare function (6), we get that the welfare function is

$$W_c(p) = \int_{\sigma p b(i,f)}^{\infty} (x - h) g(x) dx, \tag{16}$$

which is maximized when $\hat{x}_c = p_c b_c(i,f) = h$.[22] Note that maximal $b_c = \sigma f_c$ and $f_c = \bar{f}$ are part of the solution set. Since (PC_c) does not bind provided that $v < \sigma \bar{f}[1 - G(\sigma p \bar{f})]$, this solution is feasible for values of $v < \underset{\sim}{v}_{\sigma}^{c} = \sigma \bar{f}[1 - G(h)]$.

Part b. Consider the case where $\sigma \bar{f}[1 - G(h)] \leq v \leq \sigma \bar{f}[1 - G(\frac{h}{2})]$, such that (LL) and ($\text{PC}_c$) bind at the same time. Then, $w_c = 0$ and the welfare function is the same as (16). Enforcement is pinned down by (PC_c): $p_c b_c(i,f) = \hat{x}_c = G^{-1}(1 - \frac{v}{b_c(i,f)})$.

[20] The set of values i^* such that (i) $b(i^*) = \sigma f$ and (ii) the regime is corrupt is the interval $\left[\max\left[0, \frac{\sigma - \mu}{1 - \mu} f\right], \sigma f\right)$.

[21] In the parameter space $v > \tilde{v}_{\sigma}^{c}$, the solution is always interior because the interior solution requires $v > \sigma \bar{f} g(\sigma \bar{f}) \left[h - 2\sigma \bar{f} + \frac{1}{\lambda}\right] = \sigma \bar{f}[h - 2\sigma \bar{f} + 1/\lambda] \bar{f}[1 - G(\sigma \bar{f})]$ (which is always smaller than $\tilde{v}_{\sigma}^{c}$ under assumption A3) and $v < \sigma \bar{f}(h\lambda + 1)$, again always guaranteed by assumption A2.

[22] By assumption A3, $\sigma \bar{f} > h$, the solution p_c is always interior.

What is left is to determine is the equilibrium bribe and optimal fine. The equilibrium bribe is going to be maximal provided that $pb(i, f) = \sigma pf < h$ for any value of the parameters in the relevant space $\sigma\bar{f}[1-G(h)] \leq v \leq \sigma\bar{f}[1-G(\frac{h}{2})]$. That is because welfare (16) is increasing in $pb(i, f)$ if and only if $pb(i, f) < h$, and it reaches the maximum when $pb(i, f) = h$. We first show that, in the parameter space $\sigma\bar{f}[1 - G(h)] \leq v \leq \sigma\bar{f}[1 - G(\frac{h}{2})]$ we have $pb(i, f) < h$, except at $v = \sigma\bar{f}[1 - G(h)]$ where $pb(i, f) = h$ if $b(i, f) = \sigma\bar{f}$; hence, for that particular value of v the government trivially selects the maximal fine and bribe $b_c(i, f) = \sigma\bar{f}$. From the participation constraint, we have that

$$\begin{aligned} p_c b_c(i, f) &= G^{-1}\left(1 - \frac{v}{b_c(i, f)}\right) \\ &\leq G^{-1}\left(1 - \frac{\sigma\bar{f}[1 - G(h)]}{b_c(i, f)}\right) \\ &\leq G^{-1}\left(1 - \frac{\sigma\bar{f}[1 - G(h)]}{\sigma\bar{f}}\right) = h \end{aligned}$$

where the first inequality is strict iff $v \neq \sigma\bar{f}[1-G(h)]$ and it comes from the fact that the parameter space under consideration has $v \geq \sigma\bar{f}[1 - G(h)]$, and the second comes from $b(i, f) \leq \sigma f \leq \sigma\bar{f}$. Hence, both the optimal fine and the optimal bribe are maximal, i.e., $b_c(i, f) = \sigma\bar{f}$.

We conclude by noting that this solution is feasible for the space $\underset{\sim}{v}^c_\sigma \leq v \leq \tilde{v}^c_\sigma$. In that parameter space, the solution is always interior: the condition for an interior p_c is $v > \sigma\bar{f}[1 - G(\sigma\bar{f})]$ and $v < \sigma\bar{f}$. The first is always true by assumption A3 and the fact that $v > \underset{\sim}{v}^c_\sigma$, and the second is due to assumption A2. It can also be verified that at the boundary $v = \underset{\sim}{v}^{nc}_\sigma$, the solution is $\sigma p_c\bar{f} = \hat{x}_c = h$, which is the same solution found in Part c. Also, at the boundary $v = \tilde{v}^c_\sigma$, the solution is $\sigma p_c\bar{f} = \hat{x}_c = \frac{h}{2}$, which is the solution at the boundary for Part a. Outside of this interval, the solution in Part b. is dominated by the solutions in Part c. and Part a. Thus, the solution in Part b. applies to the space $\underset{\sim}{v}^c_\sigma \leq v \leq \tilde{v}^c_\sigma$, and W^*_c is continuous in v.

6.3 Proof of proposition 6

In the following proofs we use the terms *benchmark regime* and *legalized regime* as synonymies, because both regimes implement the same optimal policy and welfare. We first introduce a lemma and then use the lemma for the main proof.

Lemma 12 *For interior values of p, the regime is always clean when $\alpha > \sigma$. When $\alpha < \sigma = 1$, the regime is always corrupt.*

Proof. Intuitively, in a clean regime officers who write a fine receive an additional pay of σf and they earn αf to the government coffers. When $\alpha > \sigma$, the received fine is always larger than the pay, so for any enforcement level the government will prefer to collect the fine by providing high incentives. More formally, consider an optimal corrupt regime W^*_c with optimal policies $\tilde{p}, \tilde{f}, \tilde{\imath}, \tilde{w}$. Set the clean regime to have the following policies: $f = \tilde{f}$, $i = \sigma\tilde{f}$, $p = \sigma\tilde{p}$, and $w = \tilde{w}$. The gain in welfare from choosing this alternative policy is given by the difference between the two welfare functions (5) and (6):

$$W_{nc}(p, \tilde{w}, i, \tilde{f}) - W^*_c(\tilde{p}, \tilde{w}, \tilde{\imath}, \tilde{f}) = \sigma\tilde{p}\tilde{f}(\alpha - \sigma)[1 - G(\sigma\tilde{p}f)] + (1 - \sigma)\tilde{p}\tilde{w} > 0.$$

We now prove that when $\alpha < \sigma = 1$, the regime is always corrupt**.** When $\sigma = 1$, the bribe size is the same as the fine, which means that the corrupt regime offers as good of a deterrent as the clean regime. The superiority of the corrupt regime is guaranteed by the fact that there are no deadweight losses associated with the administration of fines. More formally, consider a corrupt regime with $i = \tilde{f}$, $p = \tilde{p}$, and $w = \tilde{w}$, where the tilde variables are the optimal choices in the optimal clean regime. Then,

$$W_c(\tilde{p}, \tilde{w}, i, \tilde{f}) - W^*_{nc}(\tilde{p}, \tilde{w}, \tilde{\imath}, \tilde{f}) = \tilde{p}\tilde{f}(1-\alpha)[1 - G(\tilde{p}\tilde{f})] > 0.$$

■

6.3.1 Part i.

Existence: Inspecting the optimal W^*_{nc} in (9), (11) and (13), it is clear that W^*_{nc} is strictly decreasing in σ only when (LL) is binding, while W^*_c is strictly increasing in σ only when (PC$_c$) is binding (see (14) and (16)). Together with lemma 12, these two facts prove existence: at low values of σ, the clean regime is preferred and at high values of σ the corrupt regime is chosen, so the two welfare functions need to cross at some intermediate σ^*, provided that W^*_{nc} and W^*_c are continuous. We thus are left to prove that W^*_{nc} and W^*_c are continuous in σ. Consider W^*_{nc}. It is clear from inspection of the welfare forms (9), (11) and (13) that they are all continuous in σ. In addition, W^*_{nc} is continuous in σ at the boundaries $\underset{\sim}{v}_{nc}$ and $\tilde{v}_{nc}$. The same applies to W^*_c as defined by (14) and (16), which is also continuous in σ at the boundary thresholds $\underset{\sim}{v}_c$ and $\tilde{v}_c$.

Uniqueness: Uniqueness requires that for any parameter value, whenever one of the two welfare functions is constant in σ the other is strictly increasing (or decreasing). The proposition thus immediately follows whenever (LL) binds in the clean regime (W^*_{nc} strictly decreasing in σ) or (PC$_c$) binds in the corrupt regime (W^*_c strictly decreasing in σ). The only special case arises when (PC$_c$) is slack in the corrupt regime and (LL) is slack in the clean regime. The former can happen only if $v < \underset{\sim}{v}_c$, while the latter arises only if $v > \tilde{v}_{nc}$. The space where these conditions hold exists iff $\frac{h}{1+\alpha} - \frac{\sigma-\alpha}{\lambda(1+\alpha)} > h$, which implies that $h < -\frac{\sigma-\alpha}{\lambda\alpha}$. But $h > \frac{\sigma-\alpha}{\lambda}$ (because we are excluding $p_{nc} = 0$ when $v < \underset{\sim}{v}^{nc}_{\sigma}$) and lemma 12 implies that we can restric attention to $\sigma \geq \alpha$. Thus, there is no parameter space where (PC$_c$) is slack in the corrupt regime and (LL) is slack in the clean regime

Having demonstrated that σ^* exists and is unique, it must be that for values of $\sigma \geq \sigma^*$ the regime is clean and for values of $\sigma < \sigma^*$ the regime is corrupt. This follows from the fact that the welfare in the clean regime is decreasing in σ and in the corrupt regime is increasing in σ.

6.3.2 Part ii.

We are left to demonstrate that $\sigma^* = \alpha$ iff $v \leq \alpha\bar{f}[1 - G(\frac{h}{1+\alpha})]$. For this proof, let $\sigma = \alpha$. First we prove that $W^*_{nc} = W^*_c$ if $v \leq \alpha\bar{f}[1-G(\frac{h}{1+\alpha})]$. Then, we show that $W^*_{nc} > W^*_c$ if $v > \alpha\bar{f}[1-G(\frac{h}{1+\alpha})]$.

case 1 $v \leq \alpha\bar{f}[1 - G(\frac{h}{1+\alpha})]$.

In this region, we have that both clean and corrupt regimes have (LL) binding. This is because, at $\alpha = \sigma$, $v < \alpha\bar{f}[1 - G(\frac{h}{1+\alpha})] = \tilde{v}_{nc} < \alpha[1 - G(\frac{h}{2})] = \tilde{v}_c$.

Evaluating clean welfare equations (11) and (13) at $\sigma = \alpha$ we have that $W^*_{nc} = \int_{\hat{x}_{nc}}^{\infty}(x - h)g(x)dx$, which is the same as W^*_c when $v < \tilde{v}_c$. Thus, $\sigma^* = \alpha$. By part (i) of the proposition, it must be that this σ^* is unique, and any regime with $\sigma > \sigma^*$ is corrupt.

case 2 $v > \alpha\bar{f}[1 - G(\frac{h}{2})]$

Next, consider the case where $v > \alpha\bar{f}[1-G(\frac{h}{2})]$, where the right-hand-side of this expression is equal to $\tilde{v}_c$ when $\sigma = \alpha$. Both clean and corrupt regimes have (LL) slack. We'll prove that $W^*_{nc} > W^*_c$, and this will imply that $\sigma^* > \alpha$ by part (i) of the proposition. Let $\hat{x}_c$ be the optimal enforcement under the corrupt regime. Consider the clean policy with (possibly sub-optimal) enforcement policy $\hat{x}_c$. It must be that $p_{nc} = \sigma p_c = \alpha p_c$. Then, $W^*_c(\hat{x}_c) - W_{nc}(\hat{x}_c) = \{\alpha\bar{f}[1-G(\hat{x}_c)] - v\}p_c(1-\alpha) < 0$. The inequality holds because we proved that (LL) is slack in the corrupt regime when $v > \alpha\bar{f}[1-G(\frac{h}{2})]$ and so $v > \alpha\bar{f}[1-G(\hat{x}_c)]$.

case 3 $\alpha\bar{f}[1-G(\frac{h}{1+\alpha})] < v \leq \alpha\bar{f}[1-G(\frac{h}{2})]$

In this case the (LL) is slack in the clean regime and both (LL) and (PC_c) bind in the corrupt regime. (Note that it cannot be that (PC_c) is slack, because $\underset{\sim}{v}_c = \alpha\bar{f}[1-G(h)] < \alpha\bar{f}[1-G(\frac{h}{1+\alpha})] < v$.) We prove that $W^*_c < W^*_{nc}$ in two steps: In step 1, we show that a clean regime can replicate the (optimal) corrupt regime by choosing the corrupt enforcement level $\hat{x}_c$; this establishes $W^*_c \leq W^*_{nc}$. In step 2, we show that the *optimal* clean regime will always favor a different enforcement level. This establishes $W^*_c \neq W^*_{nc}$. **Step 1**: Corrupt welfare is given by equation (16), $W^*_c(\hat{x}_c) = \int_{x_c}^{\infty}(x-h)g(x)dx$, where $\hat{x}_c$ is given by $v = \sigma f[1-G(\hat{x}_c)]$. Evaluating the clean regime welfare (9) at the same enforcement level, we have that $W_{nc}(\hat{x}_c) = \int_{\hat{x}_c}^{\infty}(x-h)g(x)dx$. Since the optimal enforcement in the clean regime need not be $\hat{x}_c$, $W^*_{nc} \geq W^*_c$. **Step 2:** When $v = \alpha\bar{f}[1-G(\frac{h}{1+\alpha})]$, $W^*_c = W^*_{nc}$. We show that, when we increase v above this level, enforcement decreases faster under the corrupt regime than under the clean regime, so that $\hat{x}_c \neq \hat{x}_{nc}$. This implies $W^*_c \neq W^*_{nc}$. We use total differentiation of $\hat{x}$ under the two regimes to compute $\partial p/\partial v$:

$$\frac{\partial p_c}{\partial v} = \frac{-1}{fg(pf)}\frac{1}{\sigma f}$$

and

$$\frac{\partial p_{pc}}{\partial v} = \frac{-1}{fg(pf)}\frac{1}{f(1+\alpha)+\frac{v}{1-G(pf)}}$$

where, for the latter derivative, we made use of the fact that $\frac{v}{fg(pf)} = \frac{v}{\lambda f[1-G(pf)]}$, whose derivative with respect to p is $\frac{v}{1-G(pf)}$. We thus need to prove that the former derivative is smaller than the latter in the region $\alpha\bar{f}[1-G(\frac{h}{1+\alpha})] < v \leq \alpha\bar{f}[1-G(\frac{h}{2})]$. This is so provided that $\sigma f < f(1+\alpha)+\frac{v}{1-G(pf)}$; rearranging, we have the condition $v > -f(1+\alpha-\sigma)[1-G(pf)]$, which is always the case because the right hand side is a negative number.

6.4 Proof of Proposition 7

In what follows, we prove the three statements in Proposition 7, i.e. when legalization is adopted, all miscreants self report and the optimal policy entails: (i) $i \geq \sigma f$; (ii) $r = pf$, and (iii) $w = v$.

(i) Suppose that incentives are low, such that the regime is corrupt. We have shown in the main text that the optimal a tax-and-legalize scheme must satisfy $r_c \leq pb$ in a corrupt regime. The government could provide high-powered incentives $i \geq i^{nc}$, keep the wage at w and the tax at r_c, and reduce the workforce from p to $p' = r_c/f$. Revenues and enforcement levels would not change; however, the wage bill would be smaller so the self reporting welfare function (7) would increase by $W^l_{nc}(r_c) - W^l_c(r_c) = (p-p')w = (\frac{r_c}{b} - \frac{r_c}{f})w > 0$. Thus, legalization is always implemented in a clean regime (i.e., $i \geq \sigma f$).

(ii) Suppose $r < pf$. Then, all criminals self report, and the government could slightly decrease p without changing the number of crimes. Neither the integral nor the last term in the self reporting welfare function (7) would change. The second term in (7) would decrease, because there are fewer wages to pay. Thus, welfare would increase. Since $r < pf$ is not optimal, it must be that $r \geq pf$. If $r > pf$, no one pays the tax. Thus, it must be that the optimal r is pf.

(iii) When offenders self report by paying the tax, officers never audit anyone who has committed the sanctioned act and failed to self report. They never earn any incentive pay, and the only salary paid is the base wage. Constraint PC then reduces to $w \geq v$. To maximize equation (7), the government reduces the base wage to the point where the constraint binds, to v.

6.5 Proof of proposition 9

The first part of the proof is straightforward. When $v > \tilde{v}_{\sigma}^{nc}$, the regime is either clean or corrupt (i.e., legalization implementes the same optimal policy and welfare as the clean regime.) Thus, the comparison is driven by proposition 6; thus, σ^* remains the level of σ such that the government is indifferent between the two. When $v < \tilde{v}_{\sigma}^{nc}$, we have already showed that, compared to a clean regime, legalization implements strictly higher welfare. Hence, the σ^* that separates the self reporting regime from the corrupt regime is going to be a higher value than the one that separates the clean from the corrupt.

For the second part of the proposition, consider $v < \alpha f[1 - G(h)] < \underset{\sim}{v}_{\sigma}^{c}$ and w.l.o.g. set $\sigma > \alpha$ (we need not prove the case $\sigma < \alpha$ since by proposition (6) a clean regime trivially dominates the corrupt regime.) The optimal corruption policy is to set $\hat{x}_c = \sigma p \bar{f} = h$, which yields a welfare of $W_c^*(h) = \int_h^{\infty}(x - h)g(x)dx$. Compare that welfare with the welfare derived from the legalization policy $r = h$ with associated enforcement $\hat{x}_c = p\bar{f} = h$. The increase of welfare under this policy is given by

$$W_l(\hat{x}_c) - W_c(\hat{x}_c) = [\alpha f[1 - G(h)] - v]\, p > 0$$

where the inequality is satisfied when $v < \alpha f[1 - G(h)]$ as anticipated.

Consider finally the case $v = \alpha f[1 - G(h)]$. Our previous result implies that the welfare in the corrupt and legalized regime is the same when they are both at enforcement h. However, from the first order condition (4), we have that the optimal enforcement level in the legalized regime is not h. Thus, a legalized regime dominates the corrupt regime irrespective of the strength of the institution σ, if $v \leq \alpha f[1 - G(h)]$.

7 Appendix B: Proofs not intended for publication

7.0.1 Proof of proposition 2, full policy set

We first prove statements a. and c., and then use the results to prove statement b. The proof shows the full set of optimal policies, which include (but are not limited to) policies where f is maximal.

Part a. This part is unchanged from the proof 6.1.

Part c. In the proof 6.1, we obtained the solution $p_{nc}f_{nc} = \hat{x}_{nc} = \frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}$. Let us next further characterize the solution just identified. This solution applies whenever (PC$_{nc}$) is slack; that means that $v < \sigma f_{nc}\left[1 - G\left(\frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}\right)\right]$. Since this condition is an increasing function of f, the set of v where the solution is feasible is $v < \sigma\bar{f}[1 - G(\frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)})] \equiv \underaccent{\sim}{v}^{nc}_{\sigma}$. Note also that there are many combinations of f_{nc} and p_{nc} in the parameter space $v < \underaccent{\sim}{v}^{nc}_{\sigma}$ that yield enforcement $\hat{x}_{nc}$. Specifically, for any $f \in (v/[\sigma[1 - G(\frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)})]], \bar{f}]$, the optimal number of officers is p_{nc} such that $p_{nc}f = \hat{x}_{nc} = \frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}$; under our assumptions this solution is always interior (i.e., $0 < p_{nc} < 1$). We have left to prove whether or not it is optimal to select a fine f such that $f \leq v/[\sigma[1 - G(\frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)})]]$, and, if so, what is the optimal expected penalty $\hat{x}_{nc}$. We shall study this in the next section.

Part b. This part is unchanged from the proof 6.1. Recall that, in the parameter space $v < \underaccent{\sim}{v}^{nc}_{\sigma}$, we have left to show whether or not it is optimal to select a fine f such that $f \leq v/[\sigma[1-G(\frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)})]] \equiv \hat{f}$, and, if so, what is the optimal expected penalty $\hat{x}_{nc}$. First, consider the case where $f = \hat{f}$. In this case both (PC$_{nc}$) and (LL) bind. From Part b. follows that $\hat{x}_{nc} = \frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}$, and the welfare is the same as in the case where $f < \hat{f}$ (see Part c.) Hence, the fine $f = \hat{f}$ is part of the optimal set. Now, take any $f < \hat{f}$. Part b. implies that for values of v such that $v/[\sigma[1 - G(\frac{h}{1+\alpha} - \frac{\sigma-\alpha}{\lambda(1+\alpha)})]] \leq f < \hat{f}$ optimality requires that (PC$_{nc}$) and (LL) both bind. Part b. also shows that for these values of v increasing f to the point where (PC$_{nc}$) is slack, i.e., $f > \hat{f}$, unambigously increases welfare. Hence a fine $f < \hat{f}$ in the interval considered for v cannot be optimal. Finally, for values of v such that $f < v/[\sigma[1 - G(\frac{h}{1+\alpha} - \frac{\sigma-\alpha}{\lambda(1+\alpha)})]]$, Part a. implies that optimality requires only (PC$_{nc}$) to bind. Hence, $v > \sigma f[1-G(p'f)]$, where p' is the optimal number of officers for a given fine f and v in the interval under consideration. Now find a f'' larger than f and such that $f'' \in (v/[\sigma[1-G(\frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)})]], \bar{f}]$ and a corresponding p'' such that $0 < p'' < p'$ and $p''f'' = p'f$. Compare the welfare $W_{nc}(p', f)$ and $W_{nc}(p'',f'')$, where in the latter case only (LL) binds by construction, implying that the optimal solution is as in Part c. Note that,

$$\begin{aligned} W_{nc}(p', f) - W_{nc}(p'', f'') &= -p'v + pf\alpha[1 - G(p'f)] - p''f''(\alpha - \sigma)[1 - G(p''f'')] \\ &= -p'v + p'\sigma f[1 - G(p'f)] < 0 \end{aligned}$$

where the last inequality comes from noting that in the space under consideration $v > \sigma f[1 - G(p'f)]$. Hence, we showed that a fine $f < \hat{f}$ cannot be optimal for any value of v. In summary, we showed that, in the parameter space $v < \underaccent{\sim}{v}^{nc}_{\sigma}$, the optimal fine f_{nc} is $f_{nc} \in [v/[\sigma[1 - G(\frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)})]], \bar{f}]$, and the optimal expected penalty is $\hat{x}_{nc} = \frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}$.

7.0.2 Proof of proposition 4 with full optimal policy set

Part a. This part follows the proof in 6.2.

Part c. We have shown in 6.2 that the solution is $\hat{x}_c = p_c b_c(i, f) = h$. As in the clean regime, when (PC_c) is slack p_c, f_c and i_c cannot be separately identified. Specifically, for any $b_c(i, f) \in \left(v/\sigma\left(1 - G\left(h\right)\right), \sigma\bar{f}\right]$, the optimal number of officers is p_c such that $p_c b_c(i, f) = h$. We have left to prove whether or not it is optimal to select a bribe $b_c(i, f) \leq v/\sigma\left(1 - G\left(h\right)\right)$, and, if so, what is the optimal expected penalty $\hat{x}_c$. We will study this in the next section.

Part b. The solution is the same as in 6.2.

We have left to characterize the set of optimal policies for the parameter space $v < \underaccent{\sim}{v}_\sigma^c$. Define $\hat{b} \equiv v/\sigma\left(1 - G\left(h\right)\right)$. Depending on the choice of i, f, the bribe can be larger than, equal to, or smaller than $\hat{b}$. We will show that the optimal set has $b \geq \hat{b}$.

Consider first what happens if the bribe chosen is $b(i, f) = \hat{b}$. Then, both (PC_{nc}) and (LL) bind, and the correct solution (from part b) is given by $\hat{x}_c = G^{-1}(1 - \frac{v}{b_c(i,f)}) = h$. Thus, the welfare achieved is the same as in the case where $b(i, f) > \hat{b}$ (see Part c.) Thus, the fine $b(i, f) = \hat{b}$ is part of the optimal set.

Now, take any $b(i, f) < \hat{b}$: For values of v such that $v/[\sigma[1 - G(\frac{h}{2})]] \leq b(i, f) < \hat{b}$, part c applies; thus, (PC_{nc}) and (LL) both bind. The solution is $\hat{x}_c = G^{-1}(1 - \frac{v}{b(i,f)}) < h$. Thus, the bribe $b(i, f)$ is not optimal.

For values of v such that $b(i, f) < v/[\sigma[1 - G(\frac{h}{2})]]$, part a applies; thus, only (PC_{nc}) binds. Hence, $v > b(i, f)[1 - G(b(i, f)p')]$, where p' is the optimal number of officers for a given bribe $b(i, f)$ and v in the interval under consideration. We construct a counter example bribe system that achieves a higher welfare. Specifically, choose a b'' larger than $b(i, f)$ and such that $b'' \in \left(v/\sigma\left(1 - G\left(h\right)\right), \sigma\bar{f}\right]$ and a corresponding p'' such that $0 < p'' < p'$ and $p''b'' = p'b(i, f)$. That is, b'' is in case c. Compare the welfare $W_c(p', b(i, f))$ and $W_c(p'',b'')$:

$$W_c(p', b(i, f)) - W_c(p'',b'') = -p'v + p'b(i, f)[1 - G(b(i, f)p')] < 0$$

where the last inequality comes from noting that in the space under consideration $v > b(i, f)[1 - G(b(i, f)p')]$. Hence, we showed that a bribe $b(i, f) <\hat{b}$ cannot be optimal for any value of v. In summary, we showed that, in the parameter space $v < \underaccent{\sim}{v}_\sigma^c$, the optimal bribe $b_c(i, f)$ is $b_c(i, f) \in [v/\sigma\left(1 - G\left(h\right)\right), \sigma\bar{f}]$, and the optimal expected penalty is $\hat{x}_c = h$.

7.0.3 Mathematical proof of over- and under- enforcement in the clean regime in case b and c.

Case b The claim is that, when (LL) and (PC_{nc}) both bind (alternatively, for $\underaccent{\sim}{v}_\sigma^{nc} \leq v \leq \tilde{v}_\sigma^{nc}$), there is over-enforcement in the clean regime relative to the benchmark. Note that the optimal enforcement level in case (b) solves $\sigma\bar{f}[1 - G(p_{nc}\bar{f})] = v$. Substituting this into (4) yields $p\bar{f} = \frac{h}{1+\alpha} - \frac{\sigma-\alpha}{\lambda(1+\alpha)}$, which is optimal in the benchmark regime (i.e., $p\bar{f} = p^*\bar{f}$) only when $v = \tilde{v}_{nc}$. To complete the proof, then, we need to show that as v declines below $\tilde{v}_{nc}$, enforcement increases more in the clean regime case than in the benchmark case. We use total differentiation of $\hat{x}$ under the two regimes to compute $\partial p/\partial v$[23]:

$$\frac{\partial p_{nc}}{\partial v} = \frac{-1}{fg(pf)}\frac{1}{\sigma f}$$

[23] What follows is the same proof that is used to prove proposition 6, part ii).

and

$$\frac{\partial p^*}{\partial v} = \frac{-1}{fg(pf)} \frac{1}{f(1+\alpha) + \frac{v}{1-G(pf)}}$$

where, for the latter derivative, we made use of the fact that $\frac{v}{fg(pf)} = \frac{v}{\lambda f[1-G(pf)]}$, whose derivative with respect to p is $\frac{v}{1-G(pf)}$. We thus need to prove that the former derivative is smaller than the latter in the region $\underset{\sim}{v}^{nc}_{\sigma} \leq v \leq \tilde{v}^{nc}_{\sigma}$. This is so provided that $\sigma f < f(1+\alpha) + \frac{v}{1-G(pf)}$; rearranging, we have the condition $v > -(1+\alpha-\sigma)f[1-G(pf)]$, which is always the case because the right hand side is a negative number. QED.

Case c The claim is that, when (PC_{nc}) is slack (alternatively, for $v < \underset{\sim}{v}^{nc}_{\sigma}$), there is an area of over-enforcement and an area of under-enforcement in the clean regime relative to the benchmark. In particular, for v that are close to $\underset{\sim}{v}^{nc}_{\sigma}$, the clean regime over-enforces, and for v that are significantly lower than $\underset{\sim}{v}^{nc}_{\sigma}$, the clear regime under-enforces.

Note from proposition 2 that enforcement in case c. is given by $\hat{x}_{nc} = \frac{h}{1+\alpha-\sigma} - \frac{\sigma-\alpha}{\lambda(1+\alpha-\sigma)}$. We show that this enforcement level is achievable by the honest benchmark case at a level $v = \bar{v} < \underset{\sim}{v}^{nc}_{\sigma}$. Since enforcement in the honest regime increases as v decreases, it must be the case that for there is too much enforcement for $v > \bar{v}$ and too little enforcement for $v < \bar{v}$. We start by plugging $\hat{x}_{nc}$ in the FOC for the benchmark case, equation (4). We have that

$$\frac{h(1+\alpha)}{1+\alpha-\sigma} - \frac{(\sigma-\alpha)(1+\alpha)}{\lambda(1+\alpha-\sigma)} = h - \frac{v}{fg(\hat{x}_{nc})} + \alpha/\lambda$$

Rearrange and simplify to obtain

$$\bar{v} = \frac{\sigma f[1-G(\hat{x}_{nc})]}{1+\alpha-\sigma}(1-\lambda h)$$

Note that $\bar{v} < \sigma f[1-G(\hat{x})] = \underset{\sim}{v}^{nc}_{\sigma}$ because of our assumption $h > (\sigma-\alpha)/\lambda$, which excludes the corner solution $p_{nc} = 0$.

7.0.4 Mathematical proof of over- and under-enforcement in the corrupt regime in case c.

We prove that, in the space $v < \alpha f[1-G(h)]$, the benchmark regime enforces more that the corrupt regime only when $v < \alpha f[1-G(h)](1-\lambda h)$. We show that when ($\text{PC}_{nc}$) is slack (alternatively, for $v < \underset{\sim}{v}^{c}_{\sigma}$), there is an area of over-enforcement and an area of under-enforcement in the corrupt regime relative to the benchmark regime. Corrupt enforcement is given by $\hat{x}_c = h$. The proof is based on showing that this enforcement level is optimal under the benchmark regime at a level $v = \bar{v} < \alpha f[1-G(h)]$. Since enforcement in the benchmark regime increases as v decreases, it must be the case that under the benchmark regime there is less enforcement for $v > \bar{v}$ and more enforcement for $v < \bar{v}$. We plug $\hat{x}_c = h$ in the FOC for the benchmark regime, equation (4), and solving for $\bar{v}$:

$$\bar{v} = \alpha f[1-G(h)](1-\lambda h) < \alpha f[1-G(h)]$$

8 Appendix C: Simulation Details (not intended for publication)

Given that some of our solutions are not closed-form, we simulated and solved the model numerically using Matlab. The codes are available from the authors. We set $\bar{f} = 10.1$, $v \in (0, 4)$, $\alpha = 0.5$, $h = 0.7$ (low harm act) or $h = 1.3$ (high harm act), and $\lambda = 1.2$. We used an exponential distribution function with support [0,∞). We looked at values of $\sigma \in (h/f, 1)$, which ensures that Assumption 1-3 are satisfied and the optimal number of officers p is interior. In order to solve the model numerically we discretized v, σ, and p, using respectively 40, 13 and, 10003 grid points. Increasing the number of grid points does not change our results materially. To create the 2D graphs where σ^* is depicted, we interpolated the welfare function in each regime to increase precision. Given the smoothness, continuity and monotonicity of our welfare functions in the regions under consideration, this was a harmless procedure.

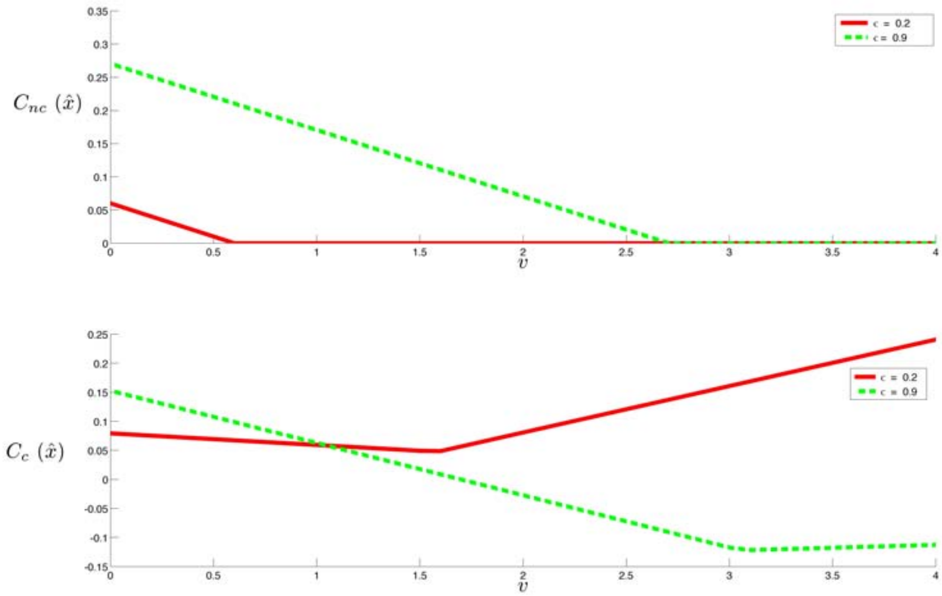

Figure 1: The cost of corruption in clean (top) and corrupt (bottom) regimes for number of officers $p = 10\%$

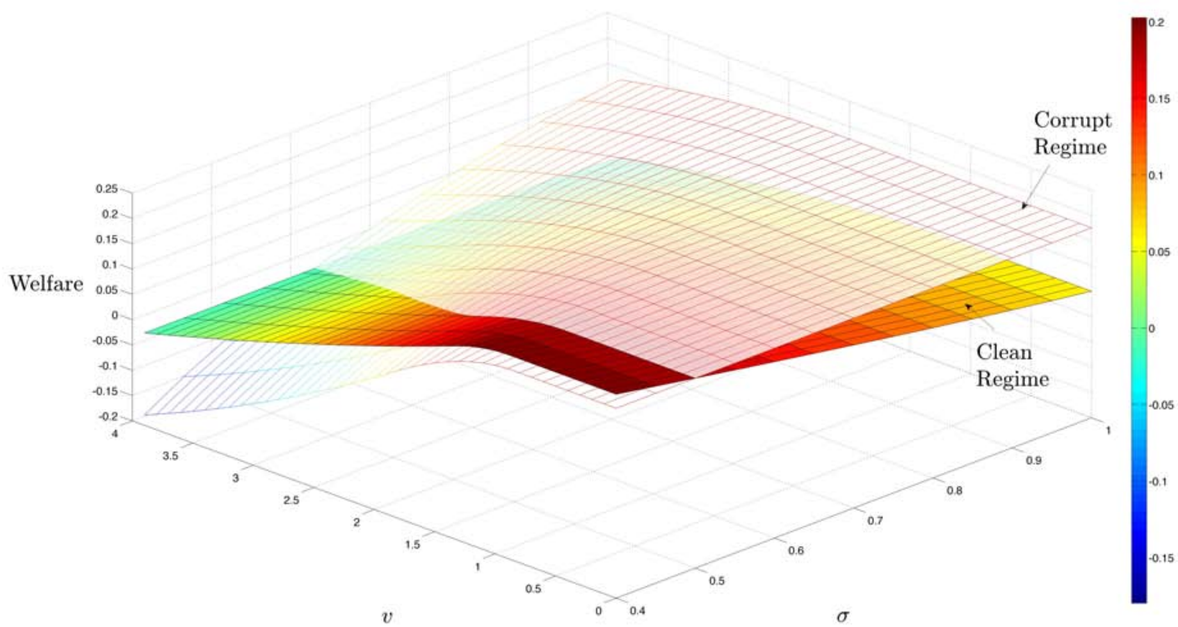

Figure 2: Optimal welfare levels, clean and corrupt regimes

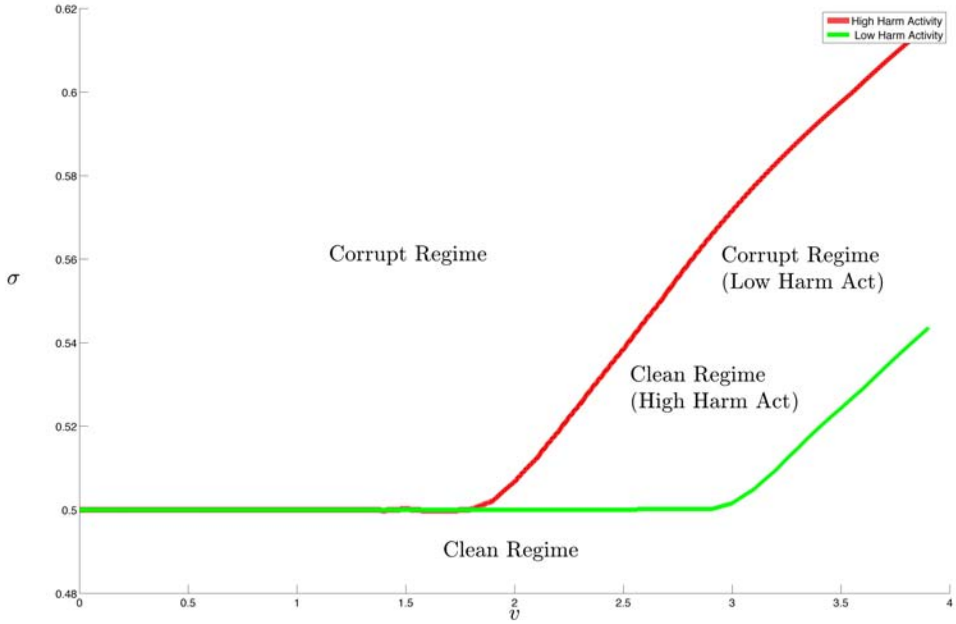

Figure 3: Optimal regime choice

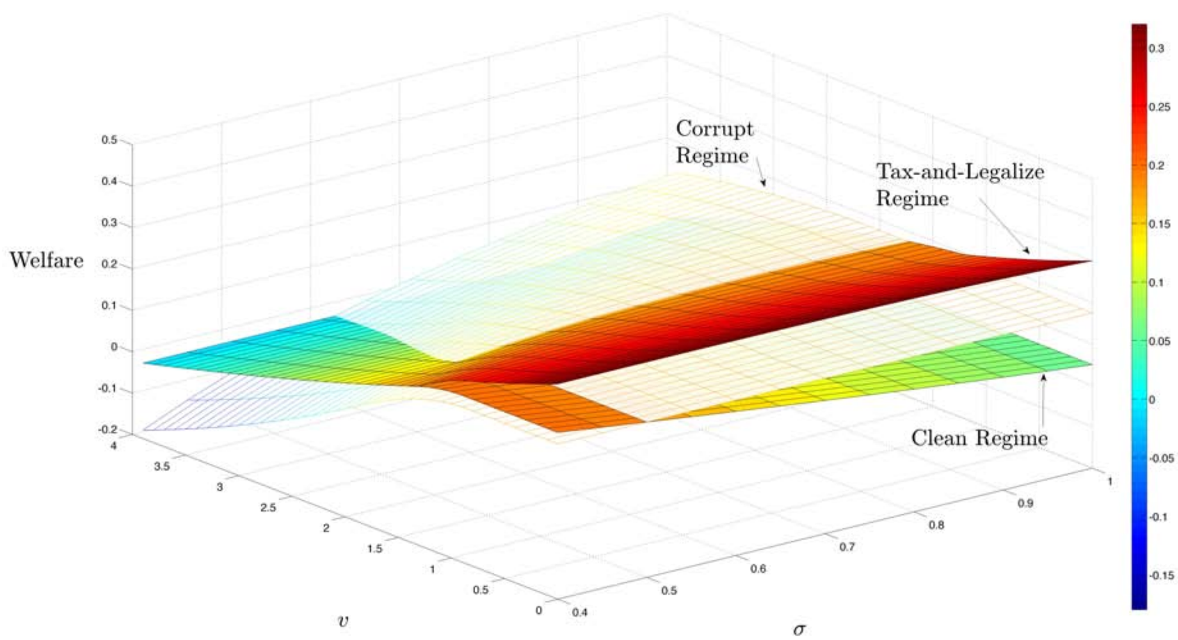

Figure 4: Optimal welfare levels and regime choice with legalization

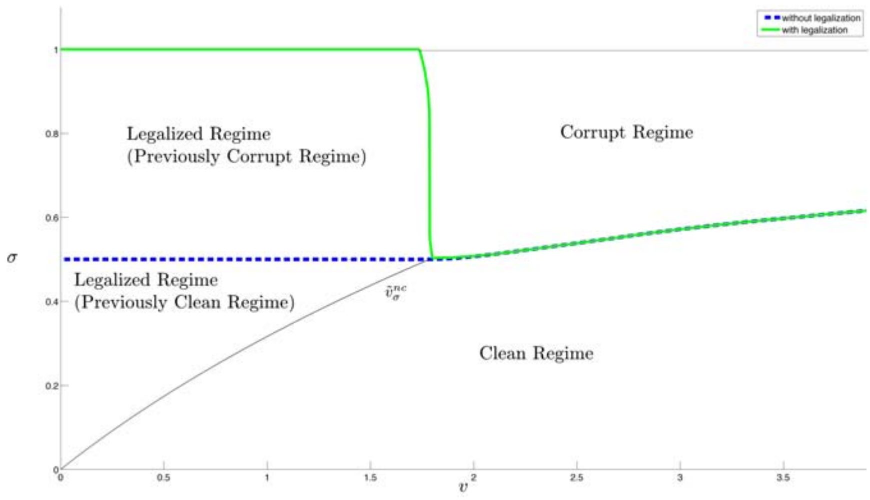

Figure 5: Regime choice with legalization, high harm activity

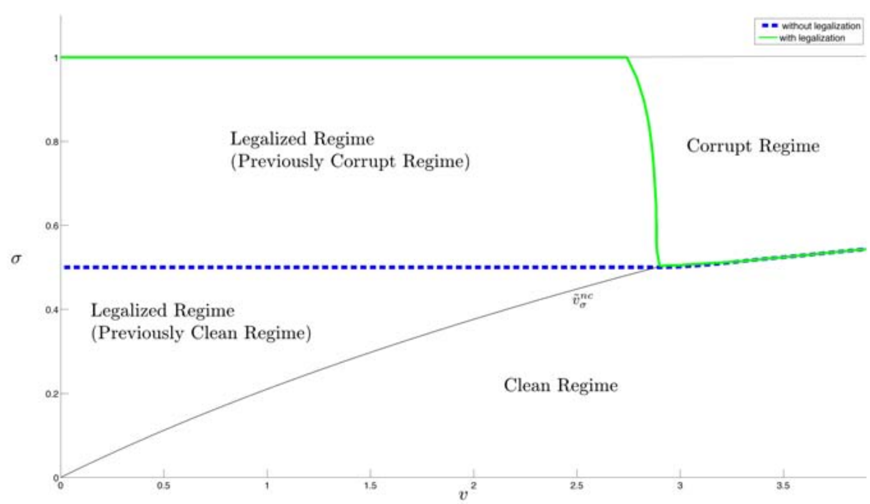

Figure 6: Regime choice with legalization, low harm activity

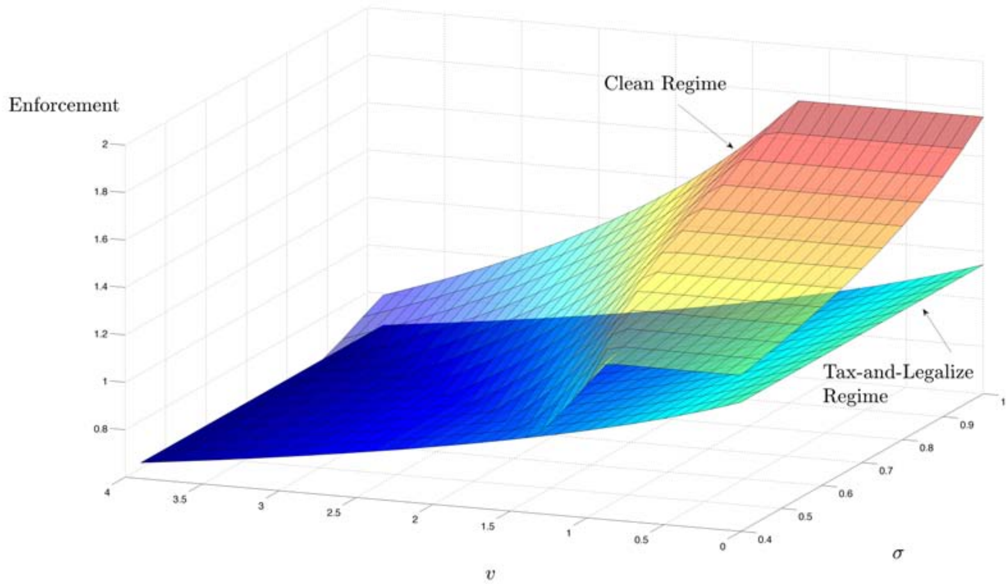

Figure 7: Enforcement level for a high harm activity, clean regime against tax-and-legalize

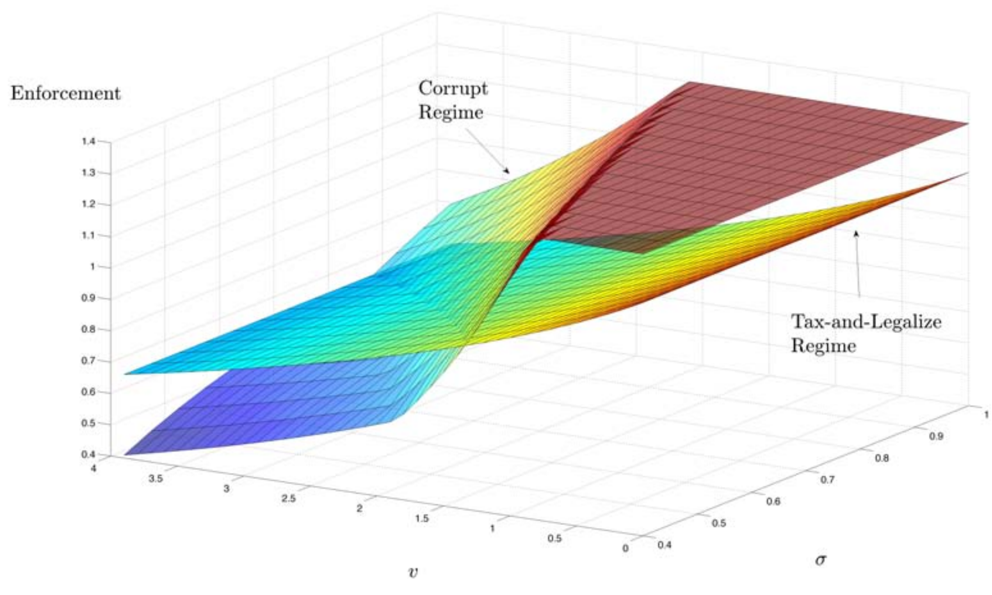

Figure 8: Enforcement level for a high harm activity, corrupt regime against tax-and-legalize

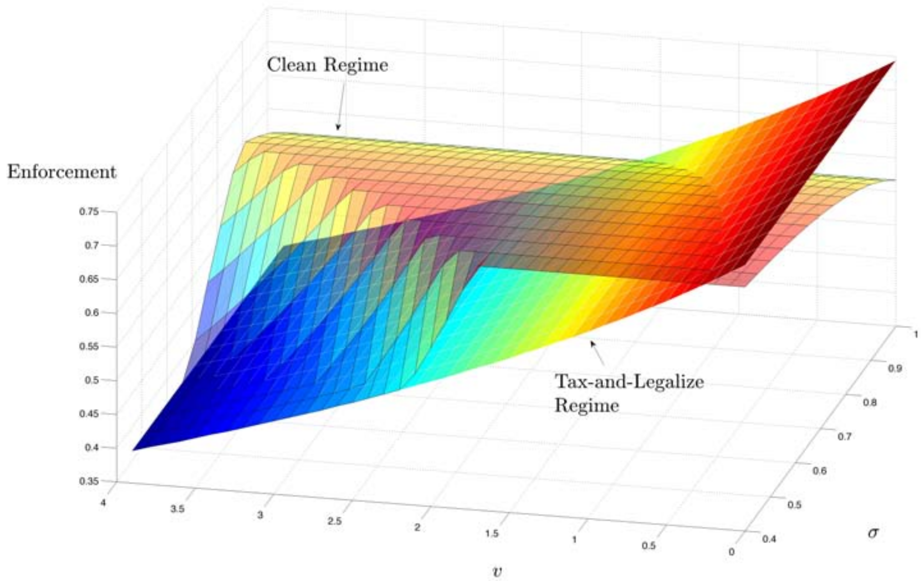

Figure 9: Enforcement level for a low harm activity, clean regime against tax-and-legalize

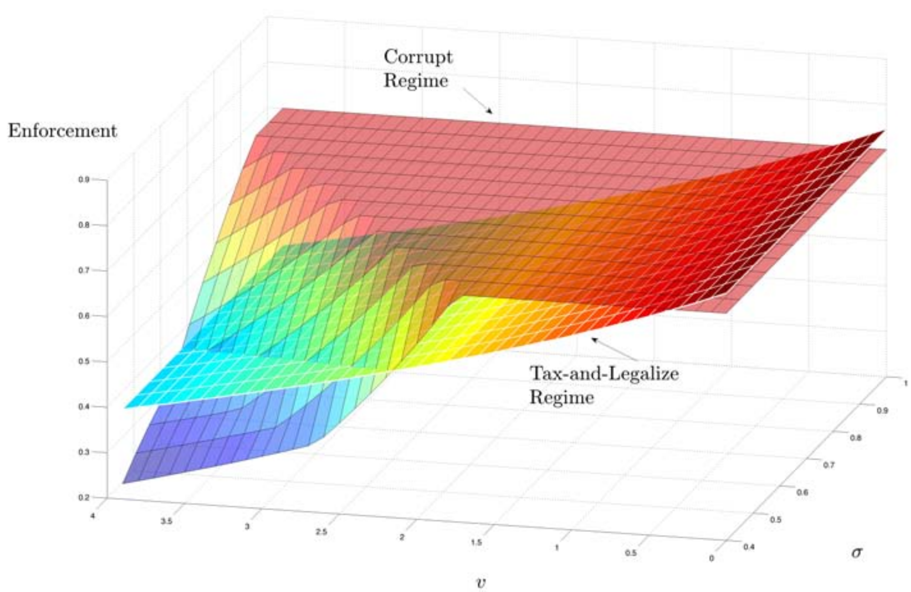

Figure 10: Enforcement level for a low harm activity, corrupt regime against tax-and-legalize

The Impact of Crime on Trust in Institutions in Mexico

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Abstract

Using survey data from the Latin American Public Opinion Project (LAPOP) and Encuesta Nacional Sobre la Inseguridad (ENSI) from Mexico during the period 2004-2010, this paper analyses the impact of insecurity and crime victimization on support and satisfaction with democracy and trust in institutions. The LAPOP data indicate perceptions of higher insecurity decrease support and satisfaction with democracy. Both the LAPOP and ENSI data indicate that perceptions of insecurity and crime victimization reduce trust in institutions, particularly in those that directly deal with crime, such as the police and judicial system. Respondents in states with higher drug-trafficking activity also have lower trust in institutions. We also find that trust in institutions has deteriorated most over time in the northeast and northwest regions.

JEL Categories: O12, O54, P48

Key Words: Insecurity, crime, violence, drug traffic, democracy, trust, social capital, institutions, Mexico

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I. Introduction

Crime in Latin America is higher than that in other regions of the world and has increased in the last two decades, making insecurity one of the most important issues in the region. While unemployment has been the main problem concerning people in Latin America (since 1995 when the Latinobarometro survey started), crime has been a growing concern in recent years. The percent of the population who believe that crime is the most important problem has risen from 9 percent in 2004 to 27 percent in 2010 (Latinobarometro, 2010).

Insecurity in Mexico has risen since President Calderon took office in late 2006 due to his efforts to fight drug cartels and reduce drug trafficking in the country. Drug turf wars have also contributed to the increase on crime. The intentional homicide rate in Mexico increased from 11 per 100,000 habitants in 2006 to 18 in 2010. The total number of homicides related to organized crime (including drug-trafficking) increased 440 percent between 2007 and 2010. According to Molzahn et al. (2012), there were around 50,000 homicides related to organized crime between 2006 and 2011. The annual number of such deaths, 8,333, is about one-third the number of annual combat deaths suffered during the Mexican Revolution of the early 20th century (Krauze and Heifetz, 1998), illustrating the magnitude of the problem and the need to deal with it. Crime has consequences for both a nation's economy and its institutional stability (Soares & Naritomi, 2010). Trust in the political system and institutions is related to social capital, and social capital is considered an engine for economic growth and development (Knack and Keefer, 1997).

This paper provides a better understanding of the connection between violence and social capital for the case of Mexico by studying the impact of insecurity on trust in institutions. This analysis expands on previous work by using a framework of repeated cross sections of surveys before (2004 and 2006) and after (2008 and 2010) periods of high levels of violence in Mexico and by incorporating techniques related to complex survey design. This paper also differs from previous work by analyzing the Encuesta Nacional Sobre la Inseguridad (ENSI), a nationally representative Mexican survey.

We find that perceptions of insecurity have a robust significant negative effect on support and satisfaction with democracy. We also show that perceptions of insecurity and crime victimization have a robust significant negative effect on trust in institutions, and particularly on trust in the police and the judicial system. We find that in trust in institutions decreases as drug trade activity increases, and it has particularly done so over time in the northwest and northeast states.

In Section II of this paper, we provide a brief overview of insecurity in Mexico in the past decade and other research on the link between insecurity and trust in institutions. In Section III, we present our data and methods, and our results are presented in Section IV. Sections V and VI presents a sensitivity analysis and discussion. Section VII concludes.

II. Literature Review

A. Insecurity in Mexico during the late 2000s

Official statistics for Mexico show that crime has risen significantly since 2006, with those states that have more illegal drug trade activity having larger increases in crime. Fighting organized crime has been a top priority for the government since Calderon took office in December 2006, with the government significantly increasing security spending and mobilizing military forces to the Mexican Border States (Beittel, 2009), which led to a significant increase on crime. The increase of crime has also been attributed to the turf wars resulting from government actions to deter organized crime, which brought instability into the structure of drug cartels. Escalante (2011) also notes that the unexpected increases in crime in 2008 and 2009 can be attributed to weak municipal police forces leading to a state of insecurity that spurs violence.

Table 1 shows the intentional homicide rates (homicides per 100,000 habitants) in recent years by state. Between 2006 and 2010, rates increased most in the border states of Chihuahua (472 percent increase in homicide rate), Nuevo Leon (350 percent increase), Coahuila (250 percent increase), Sonora (160 percent increase), Tamaulipas (100 percent increase), and Baja California (59 percent increase). Across Mexico, the intentional homicide rate increased 64 percent in these years. In contrast to the years 2006 to 2010, Table 1 shows homicide rates across Mexico decreased from 2001 to 2005. While homicide rates in Tamaulipas doubled during this time, as they also did between 2006 and 2010, only seven states showed an increase in homicide rate in these years. By contrast, between 2006 and 2010, 24 states saw their homicide rate increase.

Figure 1 presents a map showing the intentional homicide rates in 2001 (Panel A) and 2010 (Panel B). Homicide rates are presented by state in quartiles, with darker colors representing higher homicide rates. In 2010, the northern regions and those states strategic for drug tracking had higher crime rates, a geographic pattern not as evident in 2001.

Figure 2 shows states by quartiles for percentage increase of intentional homicide rates (Panel A) and organized-crime related homicides (Panel B). Increases appear to be greater in the Northwest (Baja California, Baja California Sur, Chihuahua, Sonora, Durango, Sinaloa) and Northeast (Coahuila, Nuevo Leon, Tamaulipas). Some states in the Occident region, such as Nayarit and Colima, also had high increases in their homicide rates. Altogether, these maps show that the increase on violence was concentrated in certain regions.

B. The impact of insecurity on democracy and trust in institutions

This analysis focuses on how insecurity and crime affect democracy and trust in institutions necessary for building strong political and institutional systems that increase social capital and lead to greater economic growth.[1] High levels of perceived insecurity and crime victimization might reduce support for democracy and trust in institutions. Individual perceptions of government effectiveness dealing with social issues are closely related to individual experience with their social environment and current institution. Subsequent trust is likely to depend on such experience.

The effect of insecurity and crime on support and satisfaction with democracy may be ambiguous in Latin America. Because the region has a history of authoritarian regimes, individuals might be more likely to support stronger leaders that can take authoritarian measures against crime when there is high insecurity. As Chinchilla (2002) argues, an erosion of legitimacy might justify an authoritarian government (i.e. "mano dura"). Increased insecurity can also lead individuals to be less satisfied with democracy because they are likely to have high expectations for a democratic system—and sour on democracy should insecurity increase. At the same time, other individuals may view democracy as preferable to authoritarianism regardless, and not necessarily attribute increased crime to it. For such individuals, an increase in insecurity might not affect support and satisfaction with democracy.

We expect that if individuals feel highly insecure or have been victims of crime, they will be less likely to trust current institutions and more likely to regard them as inefficient and

[1] Social capital has been associated with greater economic growth (Dearmon and Grier, 2009; Dincer and Uslaner, 2010) and greater capital accumulation (Dearmon and Grier, 2011). Social capital is also associated with better governance outcomes (Bjørnskov, 2010) and greater political accountability (Jottier and Heydels, 2012).

corrupt. Easton (1975) notes that, given longstanding discontent, individuals may eventually distrust the system entirely. Because the police are regarded as the authority responsible to ensure order, high crime rates and perceptions of insecurity will especially affect individual levels of trust in them (Weyland, 2003). For democracy to consolidate, society must regard as legitimate the political system and its institutions of authority, including the police, the judicial system, and the government (Diamond 1993, Lipset 1994, Cheibub et al., 1996). High levels of insecurity and violence would lead individuals to instead see the system as inefficient, and trust in its authorities would diminish, reducing social capital as well (Paras, 2007).

Several empirical studies, summarized in Table 2, have assessed the impact of insecurity and crime on democracy and trust in institutions for Latin American countries.[2] Many of these have shown that perceptions of insecurity have adversely affected support for democracy (Cruz 2008, Fernandez and Kuenzi 2010, Salinas and Booth 2011). Many have also shown high levels of crime victimization adversely affecting satisfaction with democracy (Fernandez and Kuenzi, 2010; Cenabou's et al., 2011, Bateson, 2010). In fact, Bateson (2012) finds that victims of crime are less likely to participate in politics. Some have specifically focused on how high levels of insecurity have adversely affected levels of trust in institutions in Central America (Perez, 2003; Cruz, 2006; and Malone, 2010).

Within Mexico, Paras and Moreno (2008) and Paras et al. (2010) found, using multivariate regression analysis, with perceptions of insecurity negatively affecting support for democracy and trust in institutions but not that for the rule of law. Earlier studies (Buendia and Moreno, 2004; Paras and Coleman, 2006) found that corruption adversely affected support for

[2] There are other studies that focus on a single Latin American country published by LAPOP. Discussion of these papers is not included for purpose of space and to put emphasis on those papers that relate to Mexico.

democracy in 2004 and that perceptions of insecurity and crime victimization adversely affected trust in institutions in 2006.

This paper adds to previous work by using available surveys between 2004 and 2010 for a repeated cross-sectional analysis and applying statistical models for complex survey data. This allows us to determine whether the relation of insecurity and crime with democracy and trust in institutions is stable over time. It also allows us to determine whether there are aggregate trends and group differences in trends, test for changing effects, and capture the net effect of social change (Firebaugh, 1997). Because crime victimization and perceptions of insecurity may be highly correlated, their empirical effects should be assessed separately.[3]

We use data from the Latin American Public Opinion Project (LAPOP) and ENSI, which complement each other (data on support and satisfaction with democracy is only provided by LAPOP surveys, but ENSI has more information related to trust in institutions). ENSI is a more comprehensive survey, with about 30,000 observations per year compared to 1,500 in LAPOP. Using ENSI helps us explore regional difference and time variation for the impact of insecurity and crime on trust in institutions. This also helps us determine whether trust in institutions is associated with drug-trafficking activity.

III. Data and Methodology

A. Data

We constructed two repeated cross sections of surveys to estimate the models in this analysis. The main datasets we used are 1) LAPOP surveys for 2004, 2006, 2008 and 2010, and

[3] In the LAPOP data, the correlation coefficient between the insecurity index and a victimization dummy variable (equal to 1 if a person is victim of crime, equal to zero otherwise) is 0.20 and is statistically significant at the 1 percent level. In the ENSI data, the correlation coefficient between the insecurity dummy variable and the victimization dummy variable is 0.14 and statistically significant at the 1 percent level as well. We will these variables further in the next section of the paper.

2) ENSI surveys collected in 2005 (ENSI-3), 2008 (ENSI-5), 2009 (ENSI-6), and 2010 (ENSI-7).[4] We describe below these surveys and their different designs and variables.

LAPOP surveys are representative at the national level for voting-age adults (18 years and older, survey covers 29 states out of 32). They have a complex sample design which includes stratification and clustering. The sample size for each wave is around 1,500 observations and is unweighted with no oversample.[5] The main variables of interest from the LAPOP survey are the following.

1) Perceptions of insecurity index. - Question: in relation to your neighborhood and the probability of being victim of a crime, how secure/insecure do you feel? Scale: 1-4; Very insecure = 4, very secure =1.
2) Crime victimization. - Question: in the last 12 months, have you been a victim of crime? Values: 0,1; victim of crime = 1, 0 otherwise.
3) Support for democracy (democracy index). - Question: democracy has problems, but it is the best form of government. Scale: 1-7; strongly disagree = 1, strongly agree = 7.
4) Support for democracy (democracy as the best political system). - Question: with which of the following sentences do you identify yourself, 1) it is the same to have a democratic system than to not have it, 2) democracy is preferable to any other form of government, and 3) in some circumstances an authoritarian government is preferable to a democratic one. This indicator is used with values 1-3 to evaluate the probability of choosing one

[4] We did not use ENSI-4, which makes reference to 2006, data because they are not representative at the national level. The reference years for ENSI surveys, which tend to be collected in the first six months of a year, are usually the year prior to data collection. For example, ENSI-3 collected data in 2005 and asked individuals whether they were a victim of crime in 2004.
[5] For more discussion on the design of the LAPOP surveys please refer to LAPOP's website (http://www.vanderbilt.edu/lapop/core-surveys.php). Note that information about the survey design for LAPOP is underdocumented.

answer over the most common answer (multinomial logit estimation is used with this dependent variable).

5) Satisfaction with democracy. - Question: in general, how satisfied or unsatisfied are you with the form in which democracy functions in Mexico. Rescaled: 1-4; highly satisfied = 4, highly unsatisfied = 1.[6]

6) Variables related to trust in institutions such as the political system, electoral system, congress, government, courts system, judicial system, police, and army. - Question: to which degree do you trust the following institution ……? Scale: 1-7, not at all=1, a lot=7.

The control variables we use in estimations including the LAPOP data are gender (female=1, male=0), civil status (relationship - married or in common law marriage=1, single, separated, divorced, widow/widower =0), have kids (have kids =1, 0 otherwise), race (two dummies: white=1 if individual identifies as white, mestiza = 1 if individual indentifies as mestiza/o), size of city (1-5, very large-capital=1, rural area=5), education (years of education completed), income level (0-10, no income=0, highest income range=10), age (number of years).[7]

ENSI surveys use complex sample design (stratification and clustering).[8] Because ENSI surveys use probability sampling for the target population of individuals 18 years or older, they

[6] Rescaled variables are those with an inverse conversion to keep consistency across the analysis. For example, for the index of satisfaction with democracy in the LAPOP survey, the data is structured as highly satisfied equals 1 and highly unsatisfied equals 4. We inversely rescale this to have an indicator that will show higher values when there is higher satisfaction with democracy.

[7] We explored but did not choose other model specifications because the fit of the model was maximized with the variables chosen. Other variables we explored were education dummies (primary, secondary, higher), urban dummy, income dummies (high level income/ medium level income), and civil status dummies (separated, divorced, widow/widower). It is also common to include age squared in this type of regressions, but when the squared term was included the linear and squared term were both insignificant.

[8] For more discussion on the design of the ENSI surveys please refer to ICESI's website (http://www.icesi.org.mx/estadisticas/estadisticas_encuestasNacionales.asp)

provide weights for the different waves at the household and individual level.[9] The number of observations for each wave ranges between 30,000 and 60,000. The ENSI variables we use are similar to those we use from the LAPOP data. The ENSI data lacks questions on support and satisfaction with democracy hence we are not able to test how perceptions of insecurity and crime affect them. We also use slightly different control variables in ENSI analysis owing to a differing structure of the survey. The ENSI data do provide more information than the LAPOP data on trust in institutions, including police. The ENSI variables we use are the following.

1) Perceptions of insecurity. - Question: do you feel insecure in your state? Values: 0,1; Feel insecure = 1, 0 otherwise.
2) Crime victimization. - Question: in the year of …… (year before the survey is taken), have you been a victim of crime in this state or another state? Values: 0,1; victim of crime=1, 0 otherwise.
3) Variables related to trust in institutions such as local police, transit police, state police (judicial), federal investigation agency (Agencia Federal de Investigacion, AFI), preventive federal police, federal police, public ministry (ministerio publico), army, and political parties.[10] Rescaled:1-4; a lot = 4, some = 3, a little = 2, none=1; Rescaled 1-3, a lot = 3, a little = 2, none=1.[11]

The control variables we use for ENSI estimations are gender (female=1, male=0), age (number of years), age squared, urban (equal to 1 if live in urban area, 0 otherwise), education

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[9] ENSI surveys are representative at the national and state level for the population 18 years and older, and in some waves they are representative at the city level.

[10] For the variable related to trust in AFI, the data was adjusted for the last wave because AFI became the ministerial federal police in 2009. This survey specifically asks individuals if they are familiar with the institution/authority for which they need to provide their level of trust. If the individual does not know the institution/authority, then there is no indicator of trust. This explains why the number of observations varies significantly in the estimations that use trust in institutions as dependent variable.

[11] When looking at trust in institutions, ENSI data uses different scales for different institutions. The scale 1-3 is typically used for authorities related to the police forces.

dummies (primary, secondary and high school, and high school more), and employment status dummies (employed and unemployed; the reference group includes those individuals not in the labor force).[12]

Variables included to control for state characteristics are GDP per capita, life expectancy, and state-level dummies.[13] We also use other state-level data to explore regional variation in the outcome variables. We used an indicator of proximity to the border was to account for regions most affected by drug trafficking. Similar to Dube et al. (2011) and Garcia-Sanchez (2011), we calculated distance between Mexican states and U.S. border cities with most activity by using latitudes and longitudes, with distance to the closest border used as an indicator of proximity to the United States.[14]

Another indicator we used is the number of criminal drug traffickers per 100,000 habitants (narco density) in the state between 1998 and 2001, as provided by Resa Nestares

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[12] For the education dummies, primary dummy is equal to 1 if the individual completed primary education, secondary and high school dummy is equal to one if the individual completed secondary or high school, and high school or more dummy is equal to one if the individual attended school at higher levels. These education dummies are not ideal because they do not distinguish between graduating from secondary and high school and attaining a higher degree. We constructed education dummies this way because ENSI-5 had limited data on education. For the employment status dummies, we include retired, stay home, and incapacitated to work individuals for the not in the labor force category. Those that did not work (besides those not in the labor force) were considered unemployed for the unemployed category, regardless of whether they were actively looking for a job because the survey does not have information on job-seeking activity. ENSI-7 does not have data on income, hence we do not include dummies controlling for income. For robustness, the model will be estimated controlling for income with the remaining ENSI waves.

[13] We constructed GDP per capita at the state level using total real GDP (2003 constant prices, from Instituto Nacional de Estadistica y Geografia, INEGI, 2011) and dividing it by total population (from Consejo Nacional de la Poblacion, CONAPO, 2011). For 2010, in which GDP per capita is not available, we extrapolated GDP per capita. We obtained data from CONAPO (2011) on life expectancy by state. We considered using other variables such as unemployment and infant mortality for controls but ultimately did not include them given their high correlations with GDP per capita and life expectancy.

[14] We obtained longitudes and latitudes of states from the Google maps distance calculator (http://www.daftlogic.com/projects-google-maps-distance-calculator.htm). We calculated distance to U.S. border cities with the most activity, as classified by Dube et al. (2011), using the great circle distance formula. Dube et al. (2011, p.13) define a major border city as one that "has an annual truck flow of at least 5,000 per year during 2002-2006, and . . . is at least 30 miles away from another major border crossing". Dube et al. identify 13 major border cities using these criteria, which we use in this analysis.

(2004).[15] We also used data provided by Secretaria de la Defensa Nacional (SEDENA, 2011) on the number of hectares of marihuana confiscated at the state level to account for illegal drug trade activity.[16] Table 3 provides summary statistics for LAPOP variables and Table 4 does so for ENSI variables.

B. Methodology

The model for the repeated cross-section of surveys is specified as

$$Y_{it} = \alpha \ + X\beta + T\gamma + \varepsilon_{it} \qquad (1)$$

Where i=1,2,…,I_t; t = 1,2,…,T. Y_{it} represents the value of the dependent variable for the i_{th} person in the t_{th} survey, α is a vector of constants, X is a 1xq vector of variables presumed to affect the dependent variable, T is a 1xT vector of time dummies for the survey years, D is a 1xD vector of state dummies, and ε_{it} is a vector of error terms for the i_{th} person in the t_{th} survey.[17] The methods of estimation used are ordered logit (ordered categorical dependent variable) for most estimations and multinomial logit (mutually exclusive categorical dependent variable). Time dummies allow us to control for time effects, while state dummies allow us to control for state characteristics that do not vary by time. We use cluster-robust standard errors with clustering by geographic areas that represent the primary sample units (PSUs, clusters) in most of the estimations. Cluster-robust standard errors allow us to deal with heteroskedasticity of the error

[15] Resa Nestares (2004) provides an indicator of "narco density" which is equal to the number of individuals that were incriminated for the production, possession, and, traffic of drugs (and other acts related to drug trafficking) per 100,000 persons who resided between 1998 and 2001 in a specific state.
[16] SEDENA (2011) provides data on the number of hectares of marihuana located, confiscated, and destroyed by the Mexican army and the air force.
[17] Note that it is not a panel data approach where individuals are followed over time. There is no data on crime victimization in Mexico that takes a dynamic panel approach.

term, where errors are correlated within clusters at the geographic level. The methodology used here is similar to Blanco's and Ruiz (2013) study for Colombia.

We also use statistical models for complex survey data when estimating the model with ENSI data. For the estimations that consider complex survey design in a repeated cross section framework, we consider the weight at the individual level and unique PSUs in each wave. We do not consider stratification because there is a problem of a stratum with a single PSU in the ENSI-3 wave. This is not a problem because using strata tends to decrease the standard errors. Thus, estimates without considering strata provide larger standard errors, resulting in a more conservative approach for evaluating significance.[18]

In the estimations using the model noted in Equation 1, the dependent variable is an indicator related to support and satisfaction with democracy and trust in institutions. The dependent variables have higher values when there is higher support and satisfaction with democracy and higher trust in institutions. The independent variables of interest are those related to perceptions of insecurity and crime victimization. The independent variable related to perceptions of insecurity has higher values for individuals who feel more insecure in the LAPOP survey. The ENSI survey, as noted, asks individuals whether they feel insecure in their state or county, with those who feel insecure assigned a value of one. Another independent variable of interest is crime victimization, which takes a value of one if the individual has been victim of a crime.

Other independent variables of interest that we include in the estimation are those regarding regional variation in illegal drug trade activity (distance to border, narco density, and confiscated marihuana). We also use two dummies for states in the northeast and northwest to

[18] For more discussion on how to apply statistical models for complex survey designs in a repeated cross section refer to http://www.stata.com/statalist/archive/2008-10/msg00521.html. More discussion on repeated cross section is also provided by Firebaugh (1997).

explore regional variation in drug trafficking. Including time dummies in the estimation allows us to determine whether there is variation over time in the dependent variables, and specifically whether there was a significant increase in crime and insecurity after 2006, when Calderon took office. We also use a variable denoting survey wave, with 0 indicating the first wave in our analysis and the latest wave. We interact this variable with the border dummy variable to test group difference in trends between the border and non-border Mexican states.[19] We only use ENSI data to test for regional and time variation because only the ENSI surveys are representative at the state level.

IV. Results

Table 5 shows LAPOP estimates for the impact of perceptions of insecurity and crime victimization on support for and satisfaction with democracy. We use an ordered logit estimator for the coefficients in columns 1-4 because the dependent variables are ordered categorical variables. Columns 1 and 2 show that the index of perception of insecurity has a robust significant negative effect at the 1-percent level on support for and satisfaction with democracy. Columns 3 and 4 shows that crime victimization does not have a statistically significant effect on support for democracy but does have a robust significant negative effect at the 1-percent level on satisfaction with democracy.

The LAPOP survey has a question that allows us to explore whether individuals are indifferent to democracy (value equal to 1), see democracy as the best system (value equal to 2), or will justify an authoritarian government in special circumstances (value equal to 3). We use multinomial logit to estimate a model for this dependent variable. In Table 5, columns 5 and 6

[19] This is similar to the approach proposed by Firebaugh (1997) to detect aggregate social trends with repeated surveys.

show the estimates for the model using the insecurity index as independent variable, and columns 7 and 8 show the estimates for the model using the victim dummy as the independent variable. These show that perceptions of insecurity have a positive effect on support for an authoritarian government. In other words, the people in Mexico might view an authoritarian government as more effective in dealing with crime. This relationship might be specific to Mexico's experience with democratization in the past decade and in recent years with high levels of violence and individuals feeling a need to a different approach to fighting crime. Our estimates also show that those individuals who were victim of a crime are more likely to be indifferent with democracy.

To estimate the impact of insecurity and crime victimization on trust in institutions, we use an ordered logit equation. This shows a robust negative effect of insecurity on trust in institutions. Specifically, Table 6 shows that as insecurity increases, trust in the political system, electoral system, congress, government, courts system, judicial system, police, and army all decrease. The largest negative effect appears to be on trust in the judicial system and the police. In other words, people feel more insecure, they are particularly less likely to trust those institutions responsible for fighting crime. Less trust in the police and the criminal justice system is also reflected in lower crime reporting.[20]

Estimates in Table 7, which include the victim dummy, are very similar to those in Table 6. Table 7 shows that being a victim of a crime has a significant negative effect on all institutions mentioned above, and particularly on trust in the judicial system and the police. The effects of victimization appear to be larger than those for insecurity on trust in the political, electoral, judicial, and courts systems, and in congress. Individuals who are victims of a crime are more

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[20] Soares (2004) presents a good analysis on the relationship between crime reporting and trust in institutions.

likely to go through the judicial and courts systems, and perhaps they are disappointed with the system based on their experience. Because a large number of crimes go unreported in Mexico, the lower trust in the courts and judicial system can be reflected on victims' perception that these systems are corrupted and inefficient and that reporting a crime to the authorities is futile.

To further understand the impact of insecurity on trust in institution, we use data from the ENSI surveys because this survey provides more detailed information about perceptions of insecurity, crime victimization, and trust in institutions. We use ordered logit estimators in assessing ENSI data because these data have a complex design with clusters and weights.

Table 8 presents estimates of the effect of perceived insecurity in the state on trust in several institutions. Insecurity has a statistically significant negative effect on all the institutions shown, with its largest effect on trust in the local police.

Table 9 shows the effects of victimization on trust in varying institutions. Being the victim of a crime has a significant negative effect at the 1-percent level on trust in all institutions but the army. Again, the greatest effect of criminal victimization is on trust in the local police.

V. Sensitivity Analysis

Our results are robust to several alternative estimations using LAPOP and ENSI data.[21] First, when entering the index of perception of insecurity and victim dummy together in the estimation, we achieve similar to those earlier noted. In these estimations, the insecurity index and the victim dummy keep their significance at least at the 5-percent level in most cases. The only difference is that the victim dummy no longer has a significant effect on trust in the army in

[21] Estimates discussed in this robustness section were not included for purpose of space, but are available upon request.

both LAPOP and ENSI models. Second, we estimated all models without state dummies, and previous results are robust in these estimations.

We used other estimations to check for robustness in ENSI data models. First, we included dummy variables that control for income and achieved similar results, albeit with lower sample size because there is no income data for ENSI-7. Second, we estimated the models using an insecurity dummy at the county level (how insecure do you feel in your county) and found similar results, albeit with larger coefficients for the insecurity dummy at the county level. Third, when using a household victimization dummy variable, we found results similar to those for individual victimization. In these estimations, the coefficients for the effects of household victimization were smaller than those found for individual victimization, which is as expected since the victim is likely to be directly affected and more traumatized from the experience. Fourth, we also estimated the model with an indicator that distinguishes whether the individual was a victim in the state of residency, again finding results similar to those discussed earlier.

The illegal drug trade and associated violence and insecurity may affect some regions in Mexico more than others over time. Accordingly, this paper seeks to determine whether the effect of drug trafficking on trust in institutions has changed over time. We use three different indicators of state-level drug trafficking activity: proximity to the United States border, number of individuals working on illegal drug trade (i.e. narco-density) that resided in the state between 1998 and 2001, and number of hectares of marihuana confiscated in the year before the reference year of the survey.

Table 10 shows the estimates including distance to the border and narco density separately in the right hand side, and their effects on trust in differing police forces.[22] Distance to

[22] In all these estimations the state dummies are not included to avoid issues of multicolinearity. Note that the index of trust in the AFI is not included in this part of the analysis since this institution changed name

the border, as shown in columns 1 through 3 has a significant positive effect on trust in local, state, and federal police, with those closer to the border having lowest trust in these police forces. Narco density, as shown in columns 4 through 6, also has a significant negative effect on trust in the local, state, and federal police. From these estimates, we can infer that greater drug trade activity is associated with lower levels of trust in the police, particularly the local police.

Confiscation of marihuana on trust in institutions positively affects trust in local, state, and preventive federal police, as shown in columns 1 through 3 of Table 11. This finding is somewhat surprising, given that more drug trade activity might lead to less trust in institutions, as in the previous equations discussed. At the same time, as the amount of marihuana confiscated increases at the state level, then trust in institutions may increase as people perceive that authorities are being effective dealing with drug trafficking.

Using repeated cross-section surveys can help us better understand variation across time. A simple way to look at time variation is to look at the significance of the time dummies. In all the estimations mentioned above, we include time dummies. In the LAPOP data, there does not seem to be a clear trend; time dummies are not significant in most cases. In the ENSI data, trust in several institutions appears to have deteriorated over time. In most cases we also observe that time dummies are positive indicating that trust was higher in previous years.

To further explore regional and time variation, we include in the estimations two dummies for those states in the northeast and northwest region, a year-trend variable, and an interaction of the year-trend variable with the regional dummies. We include these estimates in Table 11. States in the northwest region have higher levels of trust in local police, as shown in Table 11, column 6. In this estimation, the year trend and the interaction terms are negative and

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in the last ENSI survey. A question that distinguishes federal police from the preventive federal police starts in the second wave used in this analysis (ENSI-5).

statistically significant at least at the 5-percent level. The significance and sign of the interaction terms indicate that trust in the local police has been deteriorating over time for all states, but has been deteriorating at a higher rate in the northeast and northwest states. When using state and preventive federal police as dependent variables, the interaction terms are negative and statistically significant. This indicates that trust in the state and preventive federal police is deteriorating at a higher rate in the northwest and northeast regions. Results are very similar when a border dummy is included in the model (instead of the two regional dummies) and interacted with the time trend.[23]

VI. Discussion

To determine the magnitude of the effect of insecurity and crime victimization on satisfaction with democracy and trust in institutions, we estimated the marginal effect of the variables of interest (insecurity index and victim dummy) using the derivative calculation for some of the estimations discussed above.[24] For the marginal effect we calculate the average of the probability among actual persons in the data.

Using the estimates from Table 5 (columns 2 and 4), Table 12 presents the marginal effect of perceptions of insecurity and being a victim of crime on satisfaction with democracy. As individuals feel more insecure (the insecurity index increases by one unit), the probability that an individual responds that it is unsatisfied with democracy increases (index equal to 1 and 2, highly unsatisfied and unsatisfied) by 0.05 and 0.02. On the other hand, feeling more insecure reduces the probability that people are satisfied with democracy (index equal to 4 and 3, highly

[23] Results not included for purpose of space, but are available upon request.
[24] For the purpose of brevity, we focus our discussion on the marginal effect of the victim dummy using the derivative calculation. The discrete calculation of the marginal effect of the victim dummy is also possible in Stata and provides similar results (available upon request).

satisfied and satisfied) by 0.06 and 0.01 percent. The marginal effect of the victim dummy behaves in a similar way as the insecurity index, where being a victim of crime increases the probability that an individual is unsatisfied with democracy by 0.02 and 0.04, but decreases the probability that the individual is satisfied with democracy by 0.05 and 0.01.

The marginal effect of insecurity and crime victimization is also estimated for the trust in the local police and shown in Table 12 (using the coefficients shown in Tables 8 and 9, column 1). The probability that people trust a lot the local police decreases by 0.09 when people feel more insecure, and by 0.07 when people are victims of crime. The probability that the individual has no trust on the police force increases by 0.11 when people feel more insecure, and by 0.08 when people are victims of crime. It is important to note that the marginal effect of being a victim of crime does not seem to be of a greater magnitude than the impact of the perceptions of insecurity, which is surprising. One would expect that being a victim of crime would have higher negative effect on trust in institutions.

Another issue to discuss is the causal relation between trust in institutions and insecurity. One could argue that there could be a two-way causality issue, where low trust in institutions can lead to higher crime. We address for this issue in a similar way as it is done in Bateson's (2012) study. It could be argued that individual and neighborhood characteristics might affect the probability of being a victim of crime (Blattman, 2009).

We control for neighborhood effects in relation to crime by adding the organized crime and homicide rates at the state level in the previous year in the models that use satisfaction with democracy and trust in the local police as dependent variables (those models discussed in this section). We find that these additional variables are insignificant and the size and significance of the coefficients of the insecurity and victim dummy are the same as those shown previously.[25]

Another factor to control for is the level of trust in institutions at the state level in the previous year. We include in the models shown in Tables 5, columns 2 and 4, the average of the satisfaction with democracy index at the state level in the previous year calculated from the survey data. Coefficients of interest are shown in Table 13 in columns 1 and 2. The insecurity index and victim dummy continue to have a negative significant effect on satisfaction with democracy. Interestingly, the level of satisfaction with democracy at the state level in the previous year has a significant negative effect, which is surprising.

We also control for the level of trust in the local police in the previous year at the state level. Estimates shown in Table 13, columns 3 and 4, shown that our previous results are robust to the inclusion of trust in the local police in the previous year, and this additional variable has a negative coefficient but is not statistically significant.

VII. Conclusion

This analysis shows that perceptions of insecurity have a negative effect on support for democracy and trust in institutions in Mexico. Crime victimization seems to have a robust negative effect on trust in institutions, but its effect on democracy is not as robust. The detrimental effect of insecurity and crime victimization on trust in institutions appears to be greatest for those institutions that are closely related to security, such as the judicial system and the police. These findings are similar to those found by Blanco and Ruiz (2013) for Colombia.

[25] We also explore using the organized crime and homicide rates for the year of the survey and found that the coefficients of the insecurity index and victim dummy still significant. Results not included for purpose of space, but available upon request.

This analysis also shows that trust in several institutions which deal with crime has deteriorated over time, particularly in states with more drug trafficking activity.

Such analysis helps illustrate the importance of designing adequate policies to deal with the consequences of crime. Because crime seems to have a large negative effect on trust in institutions responsible for dealing with crime (police and judicial system), the lack of trust in these institutions might complicate dealing with crime in the future. If distrust in the judicial system and the police increases with insecurity, this can lead to fewer crimes being officially reported to the authorities. If crime is not reported because of distrust in institutions, then reducing crime will become more difficult.

Policy makers must understand the effects that crime and insecurity have on support and trust in institutions. To do so, they should continue to rely on victimization surveys in order to have a better understanding of crime. They should allocate resources to gather data on perceptions of insecurity, crime victimization, and experience with institutions that deal with crime appropriately and in a timely manner. A longitudinal study that provides information about individual experiences with the police and judicial system will be very valuable in determining appropriate policies for reducing crime in Mexico.

From this analysis it is also evident that trust in the local police has deteriorated significantly over time, and that the impact of insecurity has a larger negative effect on trust in this institution. This presents a significant challenge to authorities because local police are usually the first to deal with crime. Policymakers should make special efforts to improve the efficiency and reliability of local police forces.

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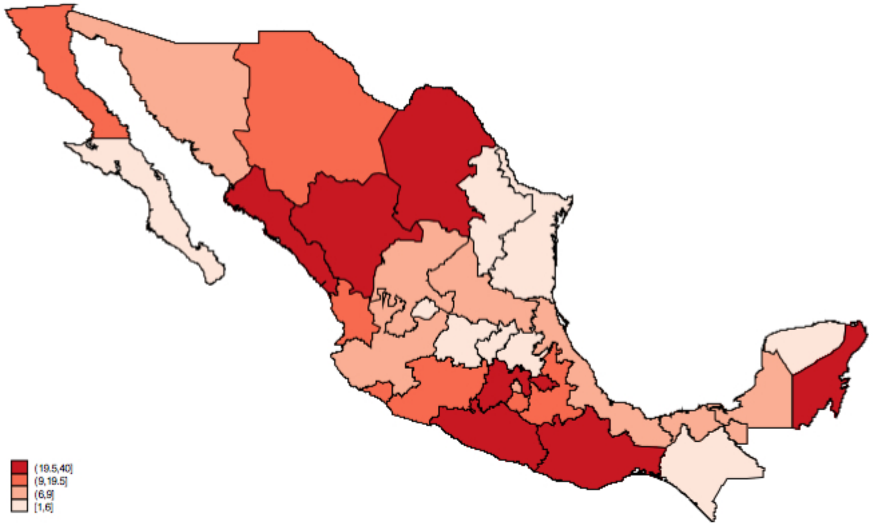
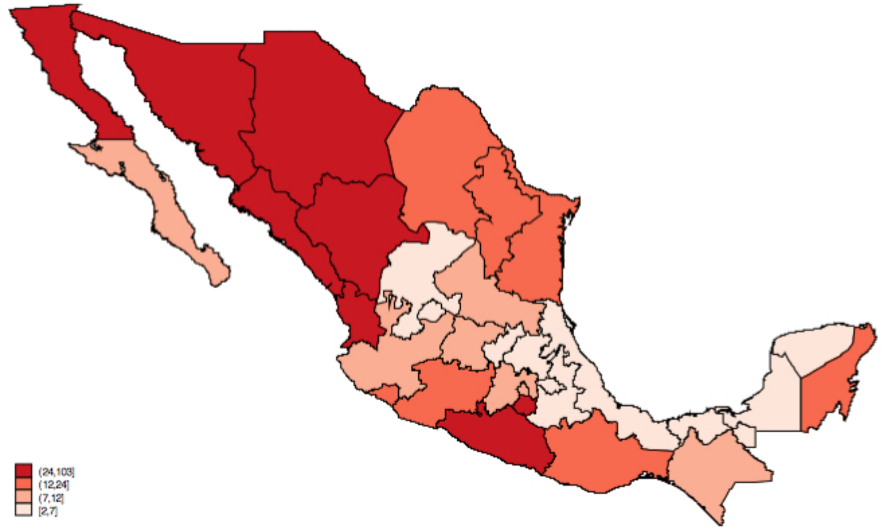
Figure 1. Intentional homicides rates

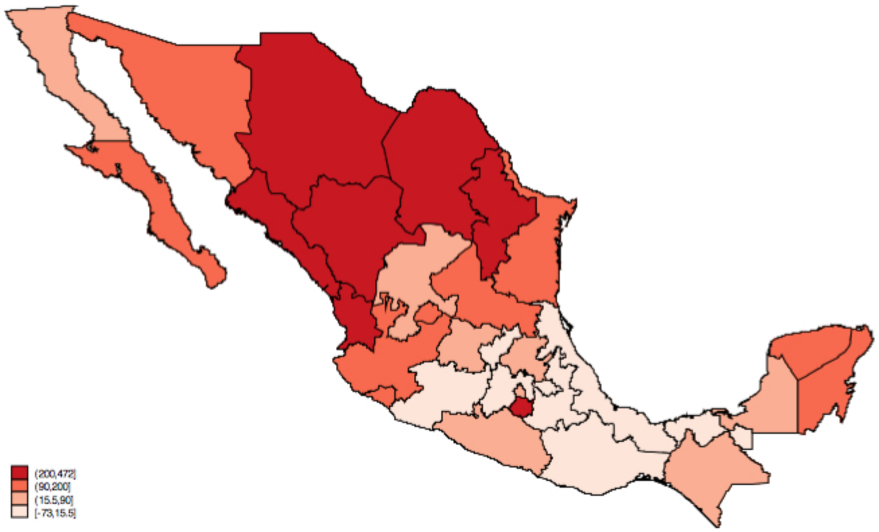


Intentional homicides rates, 2001

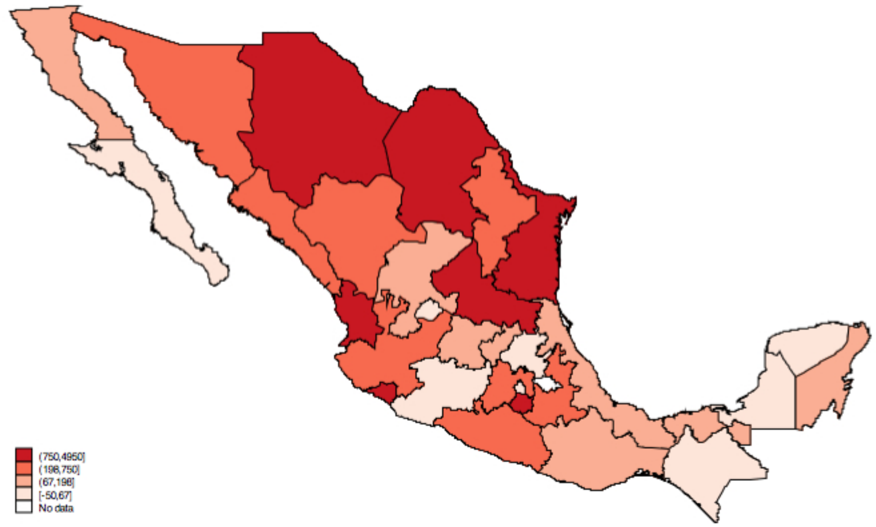


Intentional homicides rates, 2010

Figure 2. Intentional homicide rates and organized crime related homicides, percentage change



Intentional homicide rate percentage change 2006-2010



Organized crime related homicides percentage change 2007-2010

Table 1. Official Crime Statistics 2006-2010 (selected years)

		Intentional homicides[b] (per100,000)			Intentional homicides[b] (per100,000)			Org. crime homicides[c] (Total)		
State	Region[a]	2001	2005	*%change*	2006	2010	*%change*	2007	2010	*%change*
Aguascalientes	Centronorte	2	2	*0*	2	6	*200*	37	46	*24*
Baja California	Noroeste	18	19	*6*	17	27	*59*	209	540	*158*
Baja California Sur	Noroeste	6	7	*17*	4	8	*100*	6	10	*67*
Campeche	Sureste	7	7	*0*	4	7	*75*	11	14	*27*
Chiapas	Suroeste	5	6	*20*	8	10	*25*	57	77	*35*
Chihuahua	Noroeste	10	8	*-20*	18	103	*472*	244	4427	*1714*
Coahuila	Noreste	31	10	*-68*	4	14	*250*	18	384	*2033*
Colima	Occidente	16	17	*6*	5	15	*200*	2	101	*4950*
Distrito Federal	Centrosur	9	8	*-11*	7	9	*29*	182	191	*5*
Durango	Noroeste	22	12	*-45*	13	66	*408*	108	834	*672*
Guanajuato	Centronorte	5	4	*-20*	5	9	*80*	51	152	*198*
Guerrero	Suroeste	40	24	*-40*	27	48	*78*	299	1137	*280*
Hidalgo	Oriente	6	5	*-17*	4	6	*50*	43	52	*21*
Jalisco	Occidente	8	6	*-25*	6	12	*100*	70	593	*747*
México	Centrosur	22	17	*-23*	19	8	*-58*	111	623	*461*
Michoacán	Occidente	12	11	*-8*	17	18	*6*	328	520	*59*
Morelos	Centrosur	12	10	*-17*	10	33	*230*	32	335	*947*
Nayarit	Occidente	13	10	*-23*	10	38	*280*	11	377	*3327*
Nuevo León	Noreste	4	3	*-25*	4	18	*350*	130	620	*377*
Oaxaca	Suroeste	37	30	*-19*	30	14	*-53*	62	167	*169*
Puebla	Oriente	10	6	*-40*	8	7	*-13*	6	51	*750*
Querétaro	Centronorte	6	4	*-33*	3	3	*0*	5	13	*160*
Quintana Roo	Sureste	27	11	*-59*	10	22	*120*	26	64	*146*
San Luis Potosí	Centronorte	8	7	*-13*	5	12	*140*	10	135	*1250*
Sinaloa	Noroeste	21	23	*10*	23	85	*270*	426	1815	*326*
Sonora	Noroeste	8	11	*38*	10	26	*160*	141	495	*251*
Tabasco	Sureste	9	4	*-56*	8	7	*-13*	27	73	*170*
Tamaulipas	Noreste	6	12	*100*	11	22	*100*	80	1209	*1411*
Tlaxcala	Oriente	35	33	*-6*	15	4	*-73*	0	4	-
Veracruz	Oriente	7	6	*-14*	6	5	*-17*	75	179	*139*
Yucatán	Sureste	1	1	*0*	1	2	*100*	4	2	*-50*
Zacatecas	Centronorte	7	4	*-43*	4	7	*75*	18	37	*106*
National		14	11	*-21*	11	18	*64*	2829	15277	*440*

[a] Regions: Northeast = Noreste, Northwest= Noroeste, Occidente = West, Oriente = East, North-Central = Centronorte, South-Central = Centrosur, Southeastern = Sureste, and Southwestern = Suroeste.
[b] Intentional Homicides per 100,000 habitants (rounded up, official statistics). Source: Instituto Ciudadano de Estudio Sobre la Inseguridad (ICESI, 2011b). A homicide in which the death of a person is caused intentionally is considered intentional homicide.
[c] Homicides related to organized crime, total number (collection of these statistics started in 2006). Homicides considered for this category are based on the characteristics of the execution based on place, sex, age, and message. Deaths considered for this category also include deaths that resulted from attacks and confrontation between the authorities and criminal organizations, and between criminal organizations (without the presence of authority). Source: Presidencia de la Republica (2011).

Table 2. Empirical Analysis on the relationship between perceptions of insecurity and crime victimization on support and satisfaction with democracy and trust in institutions

Author	Data	Sample	Findings
Fernandez & Kuenzi (2010)	Latinobarometro 2003	17 LAC & 14 AC	PI → (-) on support and satisfaction for democracy in LAC, CV→ (-) satisfaction with democracy
Cenabou et al. (2011)	LAPOP 2006	10 LAC	CV → (-) effect on satisfaction with democracy (no effect on support)
Cruz (2008)	LAPOP 2006	21 LAC	PI → (-) effect on support for democracy PI & CV → (-) effect on rule of law
Bateson (2010)	LAPOP 2008	18 LAC	CV → (-) effect on support and trust for democracy
Bateson (2012)	LAPOP 2010	24 LAC	CV → (-) effect on support and trust for democracy
Salinas & Booth (2011)	LAPOP 2008	18 LAC	PI → (-) effect on support for democracy CV → no effect
Maldonado (2010)	LAPOP 2010	23 LAC	PI → (+) effect on government overthrow CV → no effect on government overthrow
Ahmad et al. (2011)	LAPOP 2010	26 LAC	PI & CV → trust in the police
Perez (2003)	Latinobarometro 1996 & 1998	2 CAC	PI → (-) effect on trust in the police and democracy (ELS & GTM) CV → support for military coup (ELS)
Cruz (2006)	LAPOP 1999	3 CAC	CV → (-) effect on support to the political system in all cases, PI → (-) effect only for GTM & ELS (NIC no effect)
Malone (2010)	LAPOP 2008	6 CAC	PI & CV → (-) effect in support for judicial system
Garcia (2011)	LAPOP 2005	COL	People in areas with more drug production have less trust in institutions
Buendia & Moreno (2004)	LAPOP 2004	MEX	Corruption → (-) effect on democracy
Paras & Coleman (2006)	LAPOP 2006	MEX	PI & CV → (-) effect on trust in institutions
Malone (2009)	LAPOP 2008	MEX	PI → (-) effect in support for democracy and rule of law, CV → (-) effect on the rule of law
Paras & Moreno (2008)	LAPOP 2008	MEX	PI & CV → (-) effect on trust in institutions
Paras et al (2010)	LAPOP 2010	MEX	PI → (-) effect on support for democracy PI & CV → NS effect on rule of law

LAC = Latin American countries, CAC = Central American countries, AC = African countries
PI = Perception of Insecurity, CV = Crime Victimization

Table 3. Summary Statistics – LAPOP data for 2004, 2006, 2008, and 2010

	2004			2006			2008			2010			All years	
Variable	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.	Min	Max
Insecurity index	1545	2.22	0.88	1536	2.36	0.93	1557	2.20	0.89	1553	2.32	0.92	1	4
Victim	1545	0.17	0.38	1545	0.20	0.40	1557	0.16	0.37	1562	0.26	0.44	0	1
Support democracy index	1451	5.19	1.58	1466	5.15	1.66	1488	5.11	1.74	1477	5.01	1.64	1	7
Satisfaction democracy index	1498	2.52	0.65	1479	2.47	0.68	1497	2.53	0.68	1503	2.35	0.74	1	4
Support democracy 2	1424	1.95	0.51	1357	2.00	0.52	1459	2.00	0.50	1438	2.05	0.53	1	3
Trust in the political system	1506	4.79	1.71	1504	5.15	1.68	1527	4.96	1.79	1522	4.96	1.78	1	7
Trust in the electoral system	1527	4.28	1.91	1498	5.04	1.74	1532	4.70	1.91	1532	4.44	1.95	1	7
Trust in the congress	1455	4.11	1.70	1444	4.53	1.66	1457	4.33	1.75	1461	4.24	1.71	1	7
Trust in the government	1510	4.28	1.74	1490	4.53	1.76	1530	4.59	1.79	1530	4.54	1.77	1	7
Trust in the courts system	1438	4.19	1.71	1473	4.12	1.70	1406	4.00	1.75	1452	3.80	1.62	1	7
Trust in the judicial system	1523	4.01	1.69	1512	4.04	1.75	1525	4.05	1.81	1536	3.88	1.70	1	7
Trust in the police	1530	3.55	1.88	1523	3.26	1.86	1554	3.62	1.83	1552	3.18	1.77	1	7
Trust in the army	1501	5.06	1.67	1495	5.35	1.66	1518	5.25	1.78	1513	5.33	1.68	1	7
Female	1556	0.50	0.50	1560	0.51	0.50	1560	0.51	0.50	1562	0.50	0.50	0	1
Relationship	1554	0.70	0.46	1549	0.69	0.46	1546	0.67	0.47	1559	0.63	0.48	0	1
Kids	1556	0.77	0.42	1552	0.76	0.43	1556	0.74	0.44	1547	0.72	0.45	0	1
White	1483	0.19	0.40	1465	0.23	0.42	1458	0.26	0.44	1458	0.17	0.38	0	1
Mestiza	1483	0.69	0.46	1465	0.66	0.47	1458	0.61	0.49	1458	0.73	0.44	0	1
City Size	1556	3.04	1.49	1560	3.05	1.49	1560	3.05	1.49	1562	2.93	1.43	1	5
Education	1555	8.22	4.42	1559	8.57	4.30	1560	8.27	4.47	1559	8.95	4.44	0	18
Income level	1436	4.42	2.28	1283	4.56	2.35	1346	4.58	2.31	1393	4.28	2.48	0	10
Age	1556	39.22	14.97	1558	37.61	14.31	1558	40.84	16.67	1558	39.42	15.78	18	90
GDP per capita	1556	70.43	35.61	1560	75.46	38.36	1560	77.93	39.77	1562	67.76	34.10	31.45	172.48
Life expectancy	1556	74.31	0.73	1560	74.88	0.73	1560	75.18	0.70	1562	75.46	0.70	72.58	76.50

All variables at the individual level obtained from LAPOP (2011). GDP per capita at the state level constructed using total real GDP (2003 constant prices, from Instituto Nacional de Estadistica y Geografia, INEGI, 2011) and dividing it by total population (from Consejo Nacional de la Poblacion, CONAPO, 2011). GDP per capita not available for 2010, but it was filled in with linear extrapolation. Life expectancy at the state level obtained from CONAPO (2011).

Table 4. Summary Statistics – ENSI data for 2004, 2007, 2008, and 2009

	2004			2007			2008			2009			All years	
Variable	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.	Min	Max
Victim	57398	0.11	0.32	30670	0.09	0.28	56172	0.11	0.32	60461	0.10	0.30	0	1
Insecure	55610	0.52	0.50	29534	0.57	0.49	54571	0.66	0.47	59456	0.67	0.47	0	1
Trust local police	48310	2.02	0.69	23817	1.98	0.62	37675	1.93	0.62	45133	1.87	0.56	1	3
Trust transit police	39836	1.97	0.69	22887	1.91	0.64	37584	1.88	0.64	44870	1.85	0.58	1	3
Trust state police (jud)	30526	1.96	0.74	18394	1.96	0.64	25553	1.94	0.66	12941	1.94	0.61	1	3
Trust AFI	14466	2.28	0.72	14713	2.18	0.67	19363	2.15	0.68	8600	2.07	0.62	1	3
Trust fed police(prev)	19964	2.32	0.69	15466	2.16	0.65	21635	2.15	0.66	29246	2.10	0.62	1	3
Trust federal police				28413	2.33	1.06	51312	2.26	1.10	57091	2.12	0.98	1	4
Trust public ministry				27796	1.99	0.95	50215	1.97	0.97	56492	2.02	0.93	1	4
Trust army				28726	2.81	1.09	52867	2.94	1.13	58070	2.78	1.11	1	4
Trust political parties				29671	1.59	0.82	54156	1.59	0.84	59473	1.64	0.80	1	4
Urban	57398	0.76	0.43	31088	0.83	0.38	56175	0.76	0.42	60461	0.76	0.42	0	1
Female	57398	0.55	0.50	31088	0.57	0.49	56175	0.55	0.50	60461	0.54	0.50	0	1
Age	57289	40.95	16.12	30780	41.58	16.71	55940	41.73	16.38	60145	41.85	16.62	18	97
Primary	57189	0.22	0.41	30536	0.44	0.50	56175	0.40	0.49	56144	0.22	0.41	0	1
Sec. and high school	57189	0.30	0.46	30536	0.38	0.48	56175	0.38	0.49	56144	0.24	0.43	0	1
High school more	57189	0.22	0.41	30536	0.18	0.39	56175	0.22	0.41	56144	0.39	0.49	0	1
No educ	57189	0.26	0.44	30536	0.00	0.00	56175	0.00	0.00	56144	0.15	0.36	0	1
Employed	57378	0.57	0.49	30691	0.54	0.50	56114	0.64	0.48	60456	0.57	0.50	0	1
Unemployed	57378	0.05	0.21	30691	0.01	0.10	56114	0.01	0.11	60456	0.07	0.25	0	1
Not labor force	57378	0.38	0.49	30691	0.45	0.50	56114	0.35	0.48	60456	0.37	0.48	0	1
GDP per capita	57398	78.36	63.42	31088	79.53	56.99	56175	80.84	55.47	60461	75.83	48.91	32.88	467.60
Life expectancy	57398	74.35	0.73	31088	75.01	0.66	56175	75.26	0.71	60461	75.36	0.67	72.58	76.37
Distance border	57398	750.42	362.12	31088	813.77	323.58	56175	772.67	354.31	60461	761.28	348.04	167.87	1370.17
Narco density (98-01)	57398	53.08	44.03	31088	40.71	37.44	56175	51.61	44.73	60461	50.20	42.98	4.26	143.57
Marihuaha (hec)	57398	1.01	1.62	31088	0.77	1.49	56175	1.19	2.01	60461	0.87	1.83	0	8.09
Noroeste	57398	0.26	0.44	31088	0.15	0.36	56175	0.25	0.43	60461	0.23	0.42	0	1
Noreste	57398	0.09	0.28	31088	0.10	0.29	56175	0.06	0.24	60461	0.09	0.29	0	1
Year trend	57398	0.00	0.00	31088	1.00	0.00	56175	2.00	0.00	60461	3.00	0.00	0	3

All variables at the individual level obtained from ENSI (2011). GDP per capita at the state level constructed using total real GDP (2003 constant prices, INEGI, 2011) and dividing it by total population (from CONAPO, 2011). Life expectancy at the state level obtained from CONAPO (2011). Distance to the border calculated as the distance to the closest major border city, narco density represents the number of criminals involved in drug trafficking with residency in the state, and marihuana is the number of hectares (per 1000) confiscated in the state. Year trend ranges from 0 to 3 for each survey wave (for 2004 equal to 0, for 2009 equal to 3).

Table 5. Impact of insecurity and crime victimization on democracy – LAPOP data

	Dem.supp. index (1)	Dem.sat. index (2)	Dem.supp index (3)	Dem.sat. index (4)	Indiff. model 1 (5)	Author. model1 (6)	Indiff. model2 (7)	Author. model 2 (8)
Insecurity ind.	-0.1242***	-0.3187***			0.0279	0.1152**		
	(0.0353)	(0.0401)			(0.0593)	(0.0533)		
Victim			-0.0556	-0.2319***			0.3863***	-0.0762
			(0.0741)	(0.0725)			(0.1125)	(0.1219)
Female	0.0637	0.0855	0.0436	0.0259	0.1068	-0.1755**	0.1433	-0.1802**
	(0.0511)	(0.0557)	(0.0512)	(0.0551)	(0.0878)	(0.0882)	(0.0898)	(0.0881)
Relationship	-0.0448	-0.1381	-0.0553	-0.1794**	0.0742	-0.2692**	0.0765	-0.2519**
	(0.0714)	(0.0848)	(0.0708)	(0.0847)	(0.1345)	(0.1247)	(0.1343)	(0.1248)
Kids	0.0371	-0.0261	0.0371	-0.026	-0.1165	0.1525	-0.1176	0.1551
	(0.0838)	(0.0955)	(0.0839)	(0.0943)	(0.1584)	(0.1460)	(0.1574)	(0.1477)
White	-0.0326	0.0831	-0.0335	0.0476	-0.1113	0.038	-0.0938	0.0488
	(0.1167)	(0.1249)	(0.1168)	(0.1215)	(0.1649)	(0.1961)	(0.1657)	(0.1962)
Mestizo	0.0507	0.0714	0.056	0.051	-0.2865**	-0.2095	-0.2797*	-0.2124
	(0.1005)	(0.1094)	(0.1010)	(0.1058)	(0.1448)	(0.1652)	(0.1447)	(0.1651)
City size	0.021	0.0618*	0.0412	0.0940***	0.0487	-0.002	0.047	-0.0266
	(0.0322)	(0.0360)	(0.0319)	(0.0348)	(0.0514)	(0.0520)	(0.0510)	(0.0522)
Education	0.0297***	-0.0347***	0.0327***	-0.0329***	-0.0245*	-0.0588***	-0.0285**	-0.0596***
	(0.0087)	(0.0094)	(0.0087)	(0.0094)	(0.0139)	(0.0135)	(0.0139)	(0.0135)
Income	0.0918***	0.0307*	0.0926***	0.0379**	-0.0438*	-0.0102	-0.0475**	-0.0149
	(0.0156)	(0.0164)	(0.0155)	(0.0161)	(0.0239)	(0.0262)	(0.0237)	(0.0263)
Age	0.0122***	0.0004	0.0130***	0.0011	-0.0100***	-0.0166***	-0.0097**	-0.0177***
	(0.0024)	(0.0023)	(0.0024)	(0.0023)	(0.0037)	(0.0034)	(0.0038)	(0.0034)
GDP per capita	-0.0067	0.0091	-0.0086	0.0076	-0.0376**	-0.0215*	-0.0369**	-0.0199
	(0.0116)	(0.0111)	(0.0115)	(0.0109)	(0.0168)	(0.0128)	(0.0169)	(0.0128)
Life expect.	-0.4298	-1.4763**	-0.2672	-1.1894**	-0.5799	-0.3636	-0.6538	-0.49
	(0.5171)	(0.5939)	(0.5196)	(0.5996)	(0.8010)	(0.8668)	(0.7972)	(0.8757)
Year 2004	-0.2723	-1.3536*	-0.0695	-1.0143	-0.2897	-0.8765	-0.3409	-1.0617
	(0.6286)	(0.7099)	(0.6294)	(0.7173)	(0.9624)	(1.0225)	(0.9555)	(1.0316)
Year 2006	-0.005	-0.553	0.0907	-0.3817	0.0579	-0.3639	0.0315	-0.4557
	(0.3532)	(0.3953)	(0.3542)	(0.3983)	(0.5413)	(0.5562)	(0.5373)	(0.5610)
Year 2008	0.0625	-0.1495	0.139	-0.0449	0.2877	-0.1995	0.3053	-0.2806
	(0.2221)	(0.2478)	(0.2213)	(0.2489)	(0.3508)	(0.3363)	(0.3482)	(0.3391)
Observations	4896	4950	4900	4958	4747	4747	4749	4749
Log-likelihood	-8490	-4977	-8503	-5029	-3476	-3476	-3470	-3470
Wald Chisq	211	217	190	177	246	246	257	257
R-sq(pseudo)	0.02	0.03	0.02	0.03	0.03	0.03	0.03	0.03

Coefficients with cluster-robust standard errors in parenthesis. Significance notated at * p<.1; ** p<.05; *** p<.01. Estimates for cut-off estimates and state dummies and not included for purpose of space. Ordered logit estimates in columns 1-5, and multinomial logit estimates in columns 5-8. Reference group: male, no relationship (single, separated, divorced, widow/widower), no kids, indigenous or other race, and year 2010.

Table 6. Impact of insecurity on trust on institutions – LAPOP data

	Political system (1)	Electoral system (2)	Congress (3)	Govern-ment (4)	Courts system (5)	Judicial system (6)	Police (7)	Army (8)
Insec. index	-0.1082***	-0.1843***	-0.2225***	-0.2434***	-0.2192***	-0.3146***	-0.3371***	-0.2088***
	(0.0383)	(0.0360)	(0.0330)	(0.0346)	(0.0323)	(0.0361)	(0.0347)	(0.0345)
Female	0.1168**	0.0295	-0.0232	0.0714	-0.0466	0.0364	0.0887*	-0.2689***
	(0.0525)	(0.0522)	(0.0533)	(0.0497)	(0.0542)	(0.0510)	(0.0484)	(0.0540)
Relationship	-0.0075	0.1028	-0.1007	-0.0406	0.0648	0.0249	-0.0471	-0.0548
	(0.0729)	(0.0771)	(0.0690)	(0.0693)	(0.0748)	(0.0713)	(0.0710)	(0.0738)
Kids	0.0221	-0.1204	0.1856**	0.0765	-0.1446*	0.0292	0.1029	0.1597*
	(0.0891)	(0.0837)	(0.0788)	(0.0817)	(0.0856)	(0.0829)	(0.0824)	(0.0908)
White	0.0618	0.1423	0.1696	0.1762	0.2792**	0.2195*	0.1851	-0.1575
	(0.1093)	(0.1122)	(0.1211)	(0.1258)	(0.1149)	(0.1277)	(0.1244)	(0.1192)
Mestizo	-0.0611	0.0686	0.1962*	0.0935	0.0483	0.1534	0.1247	-0.1121
	(0.0878)	(0.0966)	(0.1064)	(0.1088)	(0.0923)	(0.1055)	(0.1011)	(0.0990)
City size	0.0713*	0.0475	0.0293	0.0761**	0.0316	0.044	0.1056***	-0.0108
	(0.0368)	(0.0312)	(0.0296)	(0.0321)	(0.0331)	(0.0375)	(0.0397)	(0.0307)
Education	0.013	-0.0192**	-0.0169*	-0.0204**	-0.0264***	-0.0075	-0.0111	-0.0069
	(0.0086)	(0.0085)	(0.0086)	(0.0086)	(0.0088)	(0.0087)	(0.0085)	(0.0087)
Income	-0.0321**	0.0122	0.011	-0.0093	0.0276*	-0.0138	0.0002	0.0121
	(0.0149)	(0.0154)	(0.0152)	(0.0145)	(0.0153)	(0.0150)	(0.0157)	(0.0146)
Age	0.0076***	-0.0082***	-0.0052**	0.0013	-0.0013	0.0002	-0.0018	-0.0025
	(0.0023)	(0.0022)	(0.0023)	(0.0023)	(0.0024)	(0.0023)	(0.0022)	(0.0022)
GDP per cap.	-0.0017	-0.0275***	-0.0026	-0.0083	-0.0015	-0.0017	0.0034	-0.0307***
	(0.0087)	(0.0093)	(0.0084)	(0.0082)	(0.0093)	(0.0084)	(0.0104)	(0.0079)
Life expect.	-0.2105	-1.1596**	-0.483	-1.1779**	-1.3859***	-0.6109	-1.0180*	-1.2328***
	(0.4895)	(0.5125)	(0.4490)	(0.4924)	(0.5170)	(0.4955)	(0.5671)	(0.4358)
Year 2004	-0.4918	-1.5007**	-0.77	-1.7254***	-1.2476**	-0.6392	-0.8942	-1.7821***
	(0.5824)	(0.6371)	(0.5368)	(0.5833)	(0.6363)	(0.5928)	(0.6861)	(0.5205)
Year 2006	0.0978	0.1365	0.1353	-0.5767*	-0.4537	-0.1926	-0.6087	-0.4664
	(0.3177)	(0.3479)	(0.2931)	(0.3296)	(0.3445)	(0.3305)	(0.3740)	(0.2909)
Year 2008	-0.1125	0.1233	-0.0792	-0.3213	-0.2568	-0.1002	0.0194	-0.1925
	(0.2041)	(0.2237)	(0.1950)	(0.2212)	(0.2170)	(0.2296)	(0.2397)	(0.1961)
Observations	5016	5030	4856	5015	4786	5043	5075	4998
Log-lik.	-8936	-9278	-8924	-9192	-8782	-9307	-9276	-8480
Wald Chi sq	203.2	288.1	247.6	284.4	272.3	257.5	351.5	224.2
R-sq(pseudo)	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02

Ordered logit coefficients with cluster-robust standard errors in parenthesis. Significance notated at * p<.1; ** p<.05; *** p<.01. Estimates for cut-off estimates and state dummies and not included for purpose of space. Reference group: male, no relationship (single, separated, divorced, widow/widower), no kids, indigenous or other race, and year 2010.

Table 7. Impact of crime victimization on trust on institutions – LAPOP data

	Political system (1)	Electoral system (2)	Congress (3)	Govern-ment (4)	Courts system (5)	Judicial system (6)	Police (7)	Army (8)
Victim	-0.2314***	-0.2709***	-0.2369***	-0.2110***	-0.3143***	-0.4259***	-0.3160***	-0.1803***
	(0.0690)	(0.0655)	(0.0624)	(0.0695)	(0.0707)	(0.0642)	(0.0658)	(0.0671)
Female	0.0862	-0.0128	-0.0672	0.0258	-0.0998*	-0.0275	0.0288	-0.3027***
	(0.0526)	(0.0519)	(0.0535)	(0.0497)	(0.0539)	(0.0507)	(0.0486)	(0.0542)
Relationship	-0.0346	0.0757	-0.1211*	-0.0706	0.0316	-0.0221	-0.0958	-0.0815
	(0.0730)	(0.0772)	(0.0686)	(0.0694)	(0.0750)	(0.0720)	(0.0726)	(0.0738)
Kids	0.0338	-0.1132	0.1803**	0.0709	-0.1459*	0.0384	0.1162	0.1545*
	(0.0888)	(0.0844)	(0.0779)	(0.0815)	(0.0850)	(0.0847)	(0.0844)	(0.0912)
White	0.0578	0.1274	0.1373	0.1617	0.2562**	0.1922	0.1694	-0.1586
	(0.1090)	(0.1121)	(0.1201)	(0.1255)	(0.1163)	(0.1296)	(0.1262)	(0.1204)
Mestizo	-0.0596	0.0596	0.1785*	0.0836	0.0386	0.1399	0.1198	-0.1052
	(0.0880)	(0.0973)	(0.1049)	(0.1076)	(0.0923)	(0.1071)	(0.1008)	(0.0992)
City size	0.0817**	0.0630**	0.0514*	0.1029***	0.0513	0.0737*	0.1384***	0.0126
	(0.0361)	(0.0313)	(0.0302)	(0.0323)	(0.0335)	(0.0377)	(0.0402)	(0.0310)
Education	0.0150*	-0.0172**	-0.0136	-0.0185**	-0.0230**	-0.0028	-0.0073	-0.0039
	(0.0085)	(0.0085)	(0.0086)	(0.0087)	(0.0089)	(0.0088)	(0.0084)	(0.0087)
Income	-0.0293**	0.0181	0.0135	-0.005	0.0323**	-0.007	0.0077	0.0146
	(0.0147)	(0.0151)	(0.0150)	(0.0143)	(0.0153)	(0.0149)	(0.0157)	(0.0145)
Age	0.0076***	-0.0080***	-0.0044**	0.0021	-0.0007	0.0009	-0.0009	-0.0015
	(0.0023)	(0.0022)	(0.0022)	(0.0023)	(0.0024)	(0.0023)	(0.0022)	(0.0022)
GDP per cap.	-0.0026	-0.0294***	-0.0043	-0.0096	-0.0038	-0.0041	0.0011	-0.0313***
	(0.0088)	(0.0092)	(0.0084)	(0.0082)	(0.0095)	(0.0085)	(0.0106)	(0.0079)
Life expect.	-0.0359	-0.9946**	-0.2946	-0.9796**	-1.1526**	-0.3405	-0.658	-0.9508**
	(0.4968)	(0.5049)	(0.4558)	(0.4937)	(0.5185)	(0.4998)	(0.5637)	(0.4378)
Year 2004	-0.2985	-1.3005**	-0.5408	-1.4751**	-0.9832	-0.3414	-0.4653	-1.4459***
	(0.5896)	(0.6227)	(0.5433)	(0.5831)	(0.6372)	(0.5944)	(0.6807)	(0.5220)
Year 2006	0.2084	0.2366	0.234	-0.4531	-0.3149	-0.0426	-0.3993	-0.3166
	(0.3225)	(0.3422)	(0.2997)	(0.3323)	(0.3468)	(0.3353)	(0.3744)	(0.2935)
Year 2008	-0.0576	0.1894	0.0038	-0.2376	-0.1821	-0.0098	0.1581	-0.0929
	(0.2059)	(0.2194)	(0.1995)	(0.2215)	(0.2176)	(0.2307)	(0.2408)	(0.1967)
Observations	5022	5035	4865	5024	4794	5051	5083	5002
Log-lik.	-8950	-9298	-8964	-9233	-8811	-9362	-9342	-8519
Wald Chi sq	209.6	284.1	219.4	249.2	245.3	229.3	267.2	195.4
R-sq(pseudo)	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.01

Ordered logit coefficients with cluster-robust standard errors in parenthesis. Significance notated at * p<.1; ** p<.05; *** p<.01. Estimates for cut-off estimates and state dummies and not included for purpose of space. Reference group: male, no relationship (single, separated, divorced, widow/widower), no kids, indigenous or other race, and year 2010.

Table 8. Impact of insecurity on trust in institutions – ENSI data

	Local pol (1)	Transit pol. (2)	State pol (3)	AFI (4)	Fed pol prev (5)	Fed police (6)	Public minist (7)	Army (8)	Pol parties (9)
Insecurity index	-0.6714***	-0.5624***	-0.5415***	-0.3731***	-0.4357***	-0.4380***	-0.5718***	-0.2771***	-0.4995***
	(0.0208)	(0.0215)	(0.0270)	(0.0335)	(0.0268)	(0.0201)	(0.0203)	(0.0204)	(0.0206)
Urban	-0.4638***	-0.2609***	-0.3270***	-0.2590***	-0.1894***	-0.1102***	-0.2215***	-0.0296	-0.1844***
	(0.0296)	(0.0304)	(0.0372)	(0.0487)	(0.0375)	(0.0303)	(0.0301)	(0.0310)	(0.0306)
Female	0.0269	0.0686***	0.0253	-0.1353***	-0.2028***	-0.1636***	0.0076	-0.3114***	0.005
	(0.0224)	(0.0233)	(0.0306)	(0.0500)	(0.0406)	(0.0224)	(0.0222)	(0.0252)	(0.0252)
Age	-0.0033	-0.0057*	-0.0343***	-0.0349***	-0.0255***	-0.0208***	-0.0219***	0.004	-0.0122***
	(0.0031)	(0.0034)	(0.0044)	(0.0057)	(0.0045)	(0.0029)	(0.0029)	(0.0029)	(0.0030)
Age squared	0.0001***	0.0001***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***	-0.0001*	0.0001***
	0.0000	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Primary	-0.1627***	-0.0969**	-0.2490***	-0.2062**	-0.0525	0.052	0.0946**	0.0289	-0.0454
	(0.0382)	(0.0418)	(0.0613)	(0.0920)	(0.0569)	(0.0380)	(0.0407)	(0.0386)	(0.0400)
Sec and high	-0.1990***	-0.2026***	-0.4718***	-0.2521***	-0.062	0.0789*	0.0329	0.1532***	-0.0946**
	(0.0399)	(0.0439)	(0.0621)	(0.0947)	(0.0591)	(0.0403)	(0.0422)	(0.0407)	(0.0426)
More than high	-0.2442***	-0.2585***	-0.6757***	-0.4154***	-0.1890***	0.1199***	0.0153	0.2262***	-0.0589
	(0.0398)	(0.0428)	(0.0618)	(0.0897)	(0.0541)	(0.0390)	(0.0416)	(0.0391)	(0.0410)
Work	-0.0577**	-0.0433*	-0.0523	-0.1030*	-0.0583	-0.0137	0.0071	-0.0712***	-0.0024
	(0.0241)	(0.0250)	(0.0328)	(0.0536)	(0.0433)	(0.0236)	(0.0230)	(0.0270)	(0.0275)
No work	-0.1965***	-0.0783	-0.0739	-0.0943	-0.0425	-0.0165	-0.0549	-0.0359	-0.0023
	(0.0526)	(0.0546)	(0.0799)	(0.0985)	(0.0740)	(0.0487)	(0.0513)	(0.0508)	(0.0524)
GDP per capita	0.0018	0.0046***	0.0002	0.0023	0.0035	0.0031	0.0032	-0.0086***	0.0111***
	(0.0016)	(0.0018)	(0.0021)	(0.0031)	(0.0022)	(0.0026)	(0.0027)	(0.0028)	(0.0030)
Life expect.	0.6462***	0.9910***	1.0411***	0.2987	0.7772***	0.1496	0.341	-1.9825**	-1.1413
	(0.1695)	(0.1712)	(0.2161)	(0.2842)	(0.2354)	(0.8597)	(0.8955)	(0.9331)	(1.0216)
Year 2004	0.9880***	1.1382***	0.8247***	0.9688***	1.4073***				
	(0.1710)	(0.1716)	(0.2112)	(0.2788)	(0.2297)				
Year 2007	0.3704***	0.2597***	0.1752**	0.3002***	0.3302***	0.2812	-0.0876	-0.5740**	-0.5343*
	(0.0597)	(0.0601)	(0.0741)	(0.0959)	(0.0836)	(0.2626)	(0.2726)	(0.2863)	(0.3084)
Year 2008	0.2508***	0.0770**	0.068	0.2473***	0.2081***	0.1714	-0.1184	0.0258	-0.4009**
	(0.0374)	(0.0369)	(0.0496)	(0.0620)	(0.0501)	(0.1363)	(0.1409)	(0.1467)	(0.1616)
Observations	148000	139460	84659	55431	83426	129371	127212	131749	134916
F value	75.66	77.53	46.51	22.85	42.7	54.77	66.35	63.49	42.74

Coefficients with standard errors in parenthesis. Significance notated at * p<.1; ** p<.05; *** p<.01. Estimates for state dummies not included for purpose of space. Ordered logit estimates considering clusters and weights (no stratification; svy Stata command). Reference group: no education, not in labor force, and year 2009.

Table 9. Impact of crime victimization on trust in institutions – ENSI data

	Local pol (1)	Transit pol. (2)	State pol (3)	AFI (4)	Fed pol prev (5)	Fed police (6)	Public minist (7)	Army (8)	Pol parties (9)
Victim	-0.5107***	-0.4350***	-0.4253***	-0.3502***	-0.2843***	-0.2384***	-0.4278***	-0.0498	-0.2794***
	(0.0307)	(0.0299)	(0.0384)	(0.0475)	(0.0389)	(0.0300)	(0.0293)	(0.0314)	(0.0316)
Urban	-0.4812***	-0.2760***	-0.3264***	-0.2646***	-0.2045***	-0.1256***	-0.2410***	-0.0463	-0.2011***
	(0.0296)	(0.0300)	(0.0367)	(0.0481)	(0.0373)	(0.0302)	(0.0300)	(0.0308)	(0.0309)
Female	-0.0171	0.0294	-0.0106	-0.1633***	-0.2312***	-0.1933***	-0.0291	-0.3271***	-0.0268
	(0.0215)	(0.0223)	(0.0292)	(0.0479)	(0.0392)	(0.0215)	(0.0210)	(0.0245)	(0.0240)
Age	-0.0074**	-0.0092***	-0.0363***	-0.0367***	-0.0272***	-0.0233***	-0.0237***	0.0029	-0.0151***
	(0.0031)	(0.0033)	(0.0044)	(0.0056)	(0.0044)	(0.0028)	(0.0028)	(0.0028)	(0.0029)
Age squared	0.0001***	0.0001***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***	0.00001	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Primary	-0.1876***	-0.0998**	-0.2435***	-0.1935**	-0.0561	0.0338	0.0744*	0.0224	-0.0711*
	(0.0378)	(0.0416)	(0.0611)	(0.0909)	(0.0562)	(0.0372)	(0.0396)	(0.0380)	(0.0390)
Sec and high	-0.2160***	-0.1972***	-0.4524***	-0.2343**	-0.067	0.0644	0.0234	0.1423***	-0.1197***
	(0.0393)	(0.0434)	(0.0614)	(0.0931)	(0.0579)	(0.0393)	(0.0412)	(0.0398)	(0.0416)
More than high	-0.2386***	-0.2334***	-0.6427***	-0.3929***	-0.1848***	0.1174***	0.0273	0.2165***	-0.0702*
	(0.0394)	(0.0426)	(0.0614)	(0.0891)	(0.0540)	(0.0384)	(0.0409)	(0.0386)	(0.0404)
Work	-0.0411*	-0.0307	-0.0439	-0.0950*	-0.0515	-0.0033	0.0184	-0.0666**	0.008
	(0.0232)	(0.0242)	(0.0313)	(0.0511)	(0.0413)	(0.0226)	(0.0219)	(0.0262)	(0.0260)
No work	-0.1800***	-0.0656	-0.056	-0.1051	-0.045	-0.0166	-0.0461	-0.0356	-0.002
	(0.0520)	(0.0541)	(0.0798)	(0.0966)	(0.0726)	(0.0482)	(0.0504)	(0.0504)	(0.0514)
GDP per capita	0.0017	0.0045***	0.0005	0.003	0.003	0.0032	0.0025	-0.0085***	0.0109***
	(0.0016)	(0.0017)	(0.0021)	(0.0030)	(0.0022)	(0.0026)	(0.0027)	(0.0027)	(0.0030)
Life expect.	0.7821***	1.0991***	1.1459***	0.3497	0.8653***	0.3412	0.8573	-1.9135**	-0.7996
	(0.1690)	(0.1709)	(0.2149)	(0.2823)	(0.2339)	(0.8381)	(0.8742)	(0.9053)	(1.0100)
Year 2004	1.2090***	1.3162***	1.0011***	1.0586***	1.5444***				
	(0.1706)	(0.1713)	(0.2097)	(0.2764)	(0.2287)				
Year 2007	0.4676***	0.3373***	0.2365***	0.3184***	0.3887***	0.3678	0.1092	-0.5363*	-0.406
	(0.0595)	(0.0597)	(0.0738)	(0.0947)	(0.0819)	(0.2554)	(0.2649)	(0.2773)	(0.3031)
Year 2008	0.2891***	0.1038***	0.0927*	0.2487***	0.2344***	0.2005	-0.0323	0.0331	-0.3409**
	(0.0374)	(0.0368)	(0.0490)	(0.0616)	(0.0494)	(0.1330)	(0.1375)	(0.1424)	(0.1596)
Observations	151453	142271	86329	56420	84796	132014	129799	134630	138048
F value	58.62	65.9	41.78	22.53	39.09	43.1	49.21	60.25	31.44

Coefficients with standard errors in parenthesis. Significance notated at * p<.1; ** p<.05; *** p<.01. Estimates for state dummies not included for purpose of space. Ordered logit estimates considering clusters and weights (no stratification; svy Stata command). Reference group: no education, no labor force, and year 2009.

Table 10. Impact of insecurity on trust in institutions, regional and time variation (distance to border and narco density) ENSI data

	Local pol	State pol	Fed pol prev	Local pol	State pol	Fed pol prev
	(1)	(2)	(3)	(4)	(5)	(6)
Insecurity ind.	-0.6714***	-0.5415***	-0.4357***	-0.6714***	-0.5415***	-0.4357***
	(0.0208)	(0.0270)	(0.0268)	(0.0208)	(0.0270)	(0.0268)
Dist. border	0.0015***	0.0008***	0.0007**			
	(0.0002)	(0.0003)	(0.0003)			
Narco density				-0.0989***	-0.0525***	-0.0435**
				(0.0163)	(0.0202)	(0.0212)
Year 2004	0.9880***	0.8247***	1.4073***	0.9880***	0.8247***	1.4073***
	(0.1710)	(0.2112)	(0.2297)	(0.1710)	(0.2112)	(0.2297)
Year 2007	0.3704***	0.1752**	0.3302***	0.3704***	0.1752**	0.3302***
	(0.0597)	(0.0741)	(0.0836)	(0.0597)	(0.0741)	(0.0836)
Year 2008	0.2508***	0.068	0.2081***	0.2508***	0.068	0.2081***
	(0.0374)	(0.0496)	(0.0501)	(0.0374)	(0.0496)	(0.0501)
Observations	148000	84659	83426	148000	84659	83426
Population	1.94E+08	1.13E+08	1.13E+08	1.94E+08	1.13E+08	1.13E+08
F value	75.66	46.51	42.7	75.66	46.51	42.7

Coefficients with standard errors in parenthesis. Significance notated at * $p<.1$; ** $p<.05$; *** $p<.01$. Estimates for control variables (urban, female, age, age squared, primary, sec and high, more than high, work, no work, GDP per capita, and life expectancy) and state dummies not included for purpose of space. Ordered logit estimates considering clusters and weights (no stratification; svy Stata command). Reference group: no education, no labor force, and year 2009.

Table 11. Impact of insecurity on trust in institutions, regional and time variation (marihuana, region, and time trend) ENSI data

	Local pol (1)	State pol (2)	Fed pol prev (4)	Local pol (6)	State pol (7)	Fed pol prev (9)
Insecurity ind.	-0.6699***	-0.5413***	-0.4333***	-0.6681***	-0.5405***	-0.4357***
	(0.0208)	(0.0270)	(0.0268)	(0.0207)	(0.0270)	(0.0267)
Marihuana	0.0630***	0.023	0.1444***			
	(0.0171)	(0.0214)	(0.0216)			
Noreste				0.0438	0.3438**	-0.0904
				(0.1384)	(0.1592)	(0.1687)
Noroeste				0.2998***	0.1852	-0.1826
				(0.1061)	(0.1309)	(0.1334)
Year trend				-0.0781***	0.042	0.0465
				(0.0285)	(0.0356)	(0.0393)
Noreste*year trend				-0.1264***	-0.1421***	-0.1029***
				(0.0296)	(0.0337)	(0.0354)
Noroeste*year trend				-0.0455**	-0.0669**	-0.1416***
				(0.0201)	(0.0268)	(0.0264)
Year 2004	1.0513***	0.8567***	1.6006***			
	(0.1733)	(0.2138)	(0.2317)			
Year 2007	0.3811***	0.1824**	0.3682***			
	(0.0599)	(0.0745)	(0.0836)			
Year 2008	0.2485***	0.0696	0.2098***			
	(0.0373)	(0.0496)	(0.0499)			
Observations	148000	84659	83426	148000	84659	83426
Population	1.9E+08	1.1E+08	1.1E+08	1.9E+08	1.1E+08	1.1E+08
F value	74.2	45.55	44.88	76.06	46.33	42.83

Coefficients with standard errors in parenthesis. Significance notated at * p<.1; ** p<.05; *** p<.01. Estimates for control variables (urban, female, age, age squared, primary, sec and high, more than high, work, no work, GDP per capita, and life expectancy) and state dummies not included for purpose of space. Ordered logit estimates considering clusters and weights (no stratification; svy Stata command). Reference group: no education, no labor force, and year 2009.

Table 12. Marginal effect of insecurity and crime victimization on satisfaction with democracy and trust in the police

dy/dx				
Satisfaction with democracy	Pr(y=1)	Pr(y=2)	Pr(y=3)	Pr(y=4)
Insecurity index (T5, C2)	0.0235	0.0513	-0.0642	-0.0106
Victim dummy (T5, C4)	0.0173	0.038	-0.0476	-0.0077
Trust on local police	Pr(y=1)	Pr(y=2)	Pr(y=3)	
Insecurity index (T8, C1)	0.1104	-0.0233	-0.0871	
Victim dummy (T9, C1)	0.0844	-0.0168	-0.0677	

Table 13. Adding average of satisfaction with democracy and trust in the local police at the state level in previous year

Dependent variable	Satisfaction with democracy		Trust local police	
	(1)	(2)	(3)	(4)
Insecurity index	-0.2921***		-0.6178***	
	(0.0470)		(0.0252)	
Victim dummy		-0.2269***		-0.4993***
		(0.0819)		(0.0359)
Avg. Democ. Satis. Lag	-0.8894***	-0.8480***		
	(0.3207)	(0.3168)		
Avg. Trust Local Pol. Lag			-0.2265	-0.1952
			(0.2969)	(0.3032)
Observations	3,630	3,642	101,204	103,404

Coefficients with standard errors in parenthesis. Significance notated at * p<.1; ** p<.05; *** p<.01. Estimates in columns 1 and 2 are the same as those shown in Table 5, columns 2 and 4, with additional variable. Estimates in columns 3 and 4 are the same as those shown in Tables 8 and 9, column 1, with additional variable.

The Political Economy of Health Worker Absence: Experimental Evidence from Pakistan*

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Abstract

In many developing countries, public sector absence is both common and highly intractable. One explanation for this is that politicians provide public jobs with limited work requirements as patronage. We test this explanation for absence in Pakistan using: (i) a controlled evaluation of a novel smartphone technology designed to increase inspections at rural clinics; (ii) data on election outcomes in the 241 constituencies where the experiment took place; (iii) attendance recorded during unannounced visits and; (iv) surveys of connections between local politicians and health staff. Three results suggest that absence is linked to patronage. First, while doctors are present at 40 percent of facilities during unannounced visits in highly competitive electoral districts, they are almost always absent in captured districts. Second, doctors who know their local parliamentarian personally are present during an average of 0.727 of 3 unannounced visits, while unconnected doctors are present at 1.237 of the three visits. Last, the effects of the smartphone monitoring technology, which almost doubled inspection rates, are highly localized to competitive electoral districts.

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1 Introduction

Patronage politics often leads to the selection of inefficient policies. In clientelistic systems, politicians win office by providing targeted benefits to supporters at the cost of services which provide broader collective benefits, with negative implications for economic and human development.[1] Government jobs are commonly used for patronage. In developing countries, government workers are also frequently absent despite being generally well-compensated.[2] Moreover, public sector absence also tends to be intractable. Many policies aimed at improving attendance only work temporarily. We investigate whether the persistence of public sector absence in developing countries is linked to the use of public jobs as patronage.

Governments jobs are ideal for patronage; they can be targeted to individuals, provide a credible stream of benefits, and are reversible (Robinson and Verdier 2002). This is particularly true if politicians can minimize the actual work required in the position. Historically, jobs have been used as patronage in many settings. Chubb (1983) argues that, under the control of the Christian Democrats in Naples and Palermo during the 1950s, politicians allocated public sector jobs "on the basis of political favoritism, often having nothing to do with effective work loads or even with the actual presence of the employee in his office." Sorauf (1956) describes a similar system for road workers in Centre County, Pennsylvania and Johnston (1979) for unskilled public sector jobs in New Haven, Connecticut. Wilson (1961) describes the centrality of public jobs in maintaining the Tammany Hall political machine in New York and the Democratic Party machine in Chicago in the early 20th century. In all three settings, the beneficiaries commonly rewarded politicians with votes, party campaign

[1] Bates (1981) provides the authoritative account relating to Africa's development, arguing that African governments deliberately overvalued their exchange rates in order to subsidize politically powerful urban elites with cheaper imports at the expense of the rural poor. Khwaja and Mian (2005) and Fisman (2001) provide evidence that politicians provide preferential government benefits to firms and Dube et al. (2011) find patterns in stock returns consistent with the U.S. government providing insider information to investors about future international interventions. Dahlberg and Johansson (2002) show that the Swedish central government allocated discretionary government grants for ecologically sustainable development based primarily on the number of swing voters.

[2] We find that 68.5 percent of doctors are absent prior to our intervention. This compares with the average across Bangladesh, Ecuador, India, Indonesia, Peru and Uganda of 35 percent reported in Chaudhury et al. (2006).

work, monetary contributions, and by swinging blocs of voters.[3]

The development literature identifies public worker absence as key obstacle to delivering services to the poor (Banerjee and Duflo 2006; Chaudhury et al. 2006). With the notable exception of a camera monitoring initiative in Udaipur, Rajasthan reported in Duflo et al. (2012), absence appears unresponsive to increasing inspections, particularly when inspectors are not assisted by technologies that limit their discretion. Banerjee and Duflo (2006) review unsuccessful monitoring initiatives in Kenya and India and Banerjee et al. (2008) details the complicity of the local health administration in the failure of a monitoring initiative in rural Rajasthan. These findings support the broader position that the effects anti-corruption initiatives tend to attenuate over time (Olken and Pande 2012).

These studies propose several solutions. Duflo et al. (2012) indicate that teachers must also receive a premium for attending work; monitoring fails when workers are not paid more than their outside wage. Banerjee et al. (2008) encourage increasing senior level ownership and improving incentives for senior managers to make sure their subordinates are present. Chaudhury et al. (2006) explore the possibility of local monitoring, acknowledging that decentralized management systems may be more prone to local capture. We investigate whether public worker absence is linked to the usefulness of jobs with minimal attendance requirements for political patronage.

We examine this in three ways. First, we combine data on election outcomes in local elections with independently collected data on doctor absence. Second, we directly interview doctors to examine whether their connections to politicians are related to their job performance and to the desirability of their posting. Last, we experimentally evaluate a novel smartphone attendance monitoring program across 241 of the 297 (81 percent) of the Provincial Assembly constituencies in Punjab, examining whether impact depends on the degree of local political competition.[4]

[3]Sorauf (1956) shows that the road crew organizers were more politically active than their subordinates, arguing that the strongest supporters should be placed in jobs where they have the most influence.

[4]There are 371 seats in the Punjab Provincial Assembly. Of these, 66 are reserved for women and eight are reserved for non-muslims, leaving 297 elected seats.

This investigation yields three main results which link health service provision to local political outcomes. First, absence is more severe in less competitive districts. Second, politically connected doctors appear able to obtain better postings. Third, while the smartphone monitoring program almost doubled health worker attendance, the effects of the program are highly localized to competitive districts.

We point to two central implications. First, our data link the finding in development economics that absence is both severe and difficult to address to the observation in political science that public jobs represent a core means of patronage. Second, remedying the problem of absence faces the challenge of well-protected government jobs being an attractive means of patronage, both for politicians and constituents. This suggests that lasting improvements to health worker attendance may require strictly limiting the ability of elected politicians to interfere in the allocation of public sector jobs. Additionally, policies which reduce politicians reliance on patronage may address the problem of absence.

The paper proceeds as follows: Section 2 provides institutional details of the public health sector and describes the smartphone monitoring technology. Section 3 describes the experimental evaluation. Section 4 reviews the primary data on absence. Section 5 presents our non-experimental analysis of election outcomes and doctor absence. Section 6 provides results from the experiment and Section 7 concludes.

2 Background

2.1 The Public Health System

In Punjab province, the provision of health care services is managed by the Department of Health, which is based at the provincial headquarters in Lahore. There are five major types of facilities: (1) Basic Health Unit (BHU); (2) Rural Health Center (RHC); (3) Tehsil Headquarter Hospital[5] (THQ); (4) District Headquarter Hospital (DHQ); (5) Teaching Hospitals.

[5] In Punjab, a Tehsil is the largest sub-division of a district

We focus on Basic Health Units (BHUs). BHUs are the smallest public health care units. They are designed to be the first stop for patients seeking medical treatment in government facilities. (Hereafter in this paper, we use the word 'clinic' interchangeably to describe BHUs). There are 2496 BHUs in Punjab.[6] They largely serve rural populations; almost all such clinics are exclusively operating in rural and peri-urban areas. These clinics provide several services, including out-patient services, neo-natal and reproductive healthcare, and vaccinations against diseases. Each facility is headed by a doctor, known as the Medical Officer, who is supported by a Dispenser, a Lady Health Visitor, a School Health and Nutrition Supervisor, a Health/Medical Technician, a Mid-wife and other ancillary staff. Officially, clinics are open, and all staff are supposed to be present, from 8am to 2pm.

2.1.1 Health Sector Administration

District governments are responsible for managing local health facilities. The District Health Department is headed by an Executive District Officer who reports both to the chief bureaucrat of the district and to the most senior provincial health officials.[7] He is supported by several Deputy District Officers, typically one for each tehsil.[8] Figure 1 depicts the (simplified) health administration hierarchy in Punjab, Pakistan.

The central department has also established a parallel entity known as the Punjab Health Sector Reform Program (PHSRP). PHSRP is tasked with initiating programs to reform the primary health system with support from international and donor organizations. PHSRP is responsible for the implementation of the smartphone monitoring program we evaluate in this paper.

The Deputy District Officer is the lowest position in the officer-cadre of district health administration. He inspects all health facilities in a given Tehsil. This officer is required

[6] Each Basic Health Unit serves approximately one Union Council (Union Councils are smallest administrative units in Pakistan).

[7] The Director General of Health Services and the Secretary of the Health Department

[8] The Executive District Officer is also supported by other staff, but they are excluded for clarity because they are irrelevant to our discussion here.

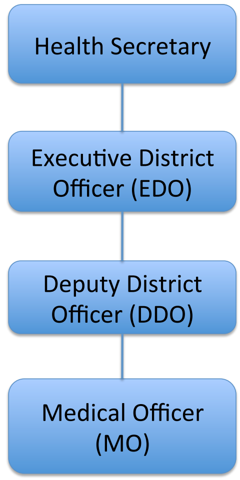


Figure 1: Health Sector Administration in Punjab

to visit every clinic at least once a month and record information collected during the visit on a standard form. The Deputy District Officer has authority to punish the clinic's absent staff by issuing a show-cause notice, suspension and withholding pay (in case of contract staff). The Executive District Officer relies entirely on this subordinate officer to ensure staff presence. As the administrative head of the health department in the district, the Executive District Officer desires smooth functioning of the setup at minimum acceptable level. He relies on the Deputy District Officer to ensure this smooth function by sanctioning underperforming facilities in terms of staff attendance, medicine availability and cleanliness etc.

2.1.2 Career Concerns and Internal Agency Problems

The Executive District Officer faces a severe agency problem in managing his deputy inspectors. This is for several reasons. First, he has limited visibility into the inspectors' activities. Second, he has only two weak means of sanctioning an inspector. He can either issue a verbal reprimand or, in serious cases, send a written request for investigation to provincial authorities. The investigation process is long, highly bureaucratic, and prone to interference by elected politicians.

The career concerns of the Executive District Officer and his deputy inspectors are also fundamentally different. The Executive District Officer reports directly to senior provincial authorities who face few bureaucratic hurdles to sanctioning and hold him directly accountable for service delivery in his district. Performance for the EDO is commonly rewarded with appointment to a higher office. In contrast, the Deputy District Officers are neither officially nor practically accountable for health service delivery. Appointees to this position have to serve for years before they are considered for promotion to the next level in the district. This lack of opportunity to move to a leadership position outside of the district setup diminishes immediate interest in improving the outcomes in the Tehsil, and creates misaligned interests between them and the Executive District Officers.

2.1.3 Doctors and Politicians

Influence over public sector positions provide politicians two means of patronage. First, politicians help health officials obtain postings in their region of choice (usually their home union council). Second, once posted, health officials also appeal to politicians for protection against suspension, transfer, and other sanctions for underperformance.

Many staff members belong to politically powerful clans and families. These staff can provide three types of favors to politicians. First, they can activate their networks to mobilize votes. Second, health staff are commonly recruited to assist the election commission with drawing up voter lists and overseeing polling on election day. Third, they can provide preferential care to supporters or condition care on support.

2.2 Smartphone Monitoring

Our project attempts to explore the use of audits by government monitors as a solution to the problem of absence. As in Duflo et al. (2012), we explore a technology-based initiative that seeks, in part, to detect absence. There is increasing interest in using ICT to rapidly collect information that is useful to auditors. Solving intra-bureaucracy agency problems is a potential application. We implement a smartphone-based solution that allows health system inspectors to upload the results of their assigned visit to a basic health facility to an aggregating website (dashboard), which instantly updates reports at different levels of aggregation (zonal and provincial) with the information captured by this most recent visit.

The “Monitoring the Monitors” program replaced the traditional paper-based monitoring system, which collects data on facility utilization, resource availability, and worker absence, with an android-based smartphone application. Data are transmitted to a central database using a General Packet Radio Service (GPRS) in real time. Data are then aggregated and summary statistics, charts, and graphs are presented in a format designed in collaboration with senior health officials. That data are: (i) aggregated in the province in real time; (ii) geo-tagged, time-stamped, and complemented with facility staff photos to check for reliability; and (iii) available in real time to district and provincial officers through an online dashboard. Figure 2 shows one view of the online dashboard.

Application development started in August 2011. After developing the application and linking it to a beta version of the online dashboard, the system was piloted in the district of Khanewal. We remove Khanewal district from the experimental sample. Health administration staff were provided with smartphones and trained to use the application. The main purpose of the pilot was to ensure that the technology was working and to refine the application and the dashboard. During the pilot, several inspectors requested that the program require pictures of all staff in attendance, not just the inspector because they thought it might reduce pressure from health staff to falsify attendance.

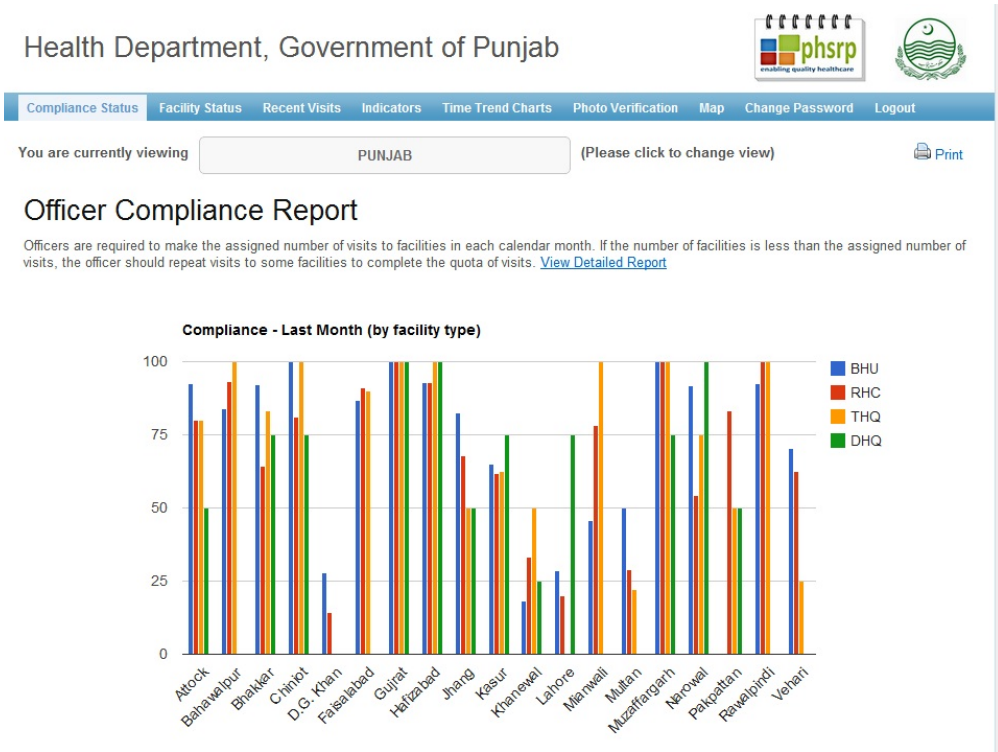


Figure 2: Online Dashboard - Summary of Inspection Compliance by District

3 Experiment

Our experimental sample comprised all health facilities in the district of Punjab, which has a population of 100 million. Tens of millions of public sector health users therefore stood to benefit from the program. We randomly implemented the program in 18 of the 35 districts in our experimental sample. In assigning treatment we stratified on baseline attendance (from primary or secondary data) and the number of clinics in a district to ensure a roughly even number of treatments and controls. Figure 3 depicts control and treatment districts.

We randomized at the district level. The intervention channels information about inspections to district health officials; randomization at a finer level is therefore very likely to generate externalities. The Department of Health also determined that sub-district randomization was not administratively feasible. Cluster randomization also allays some concerns about externalities generated by interactions between inspectors in the same district. All

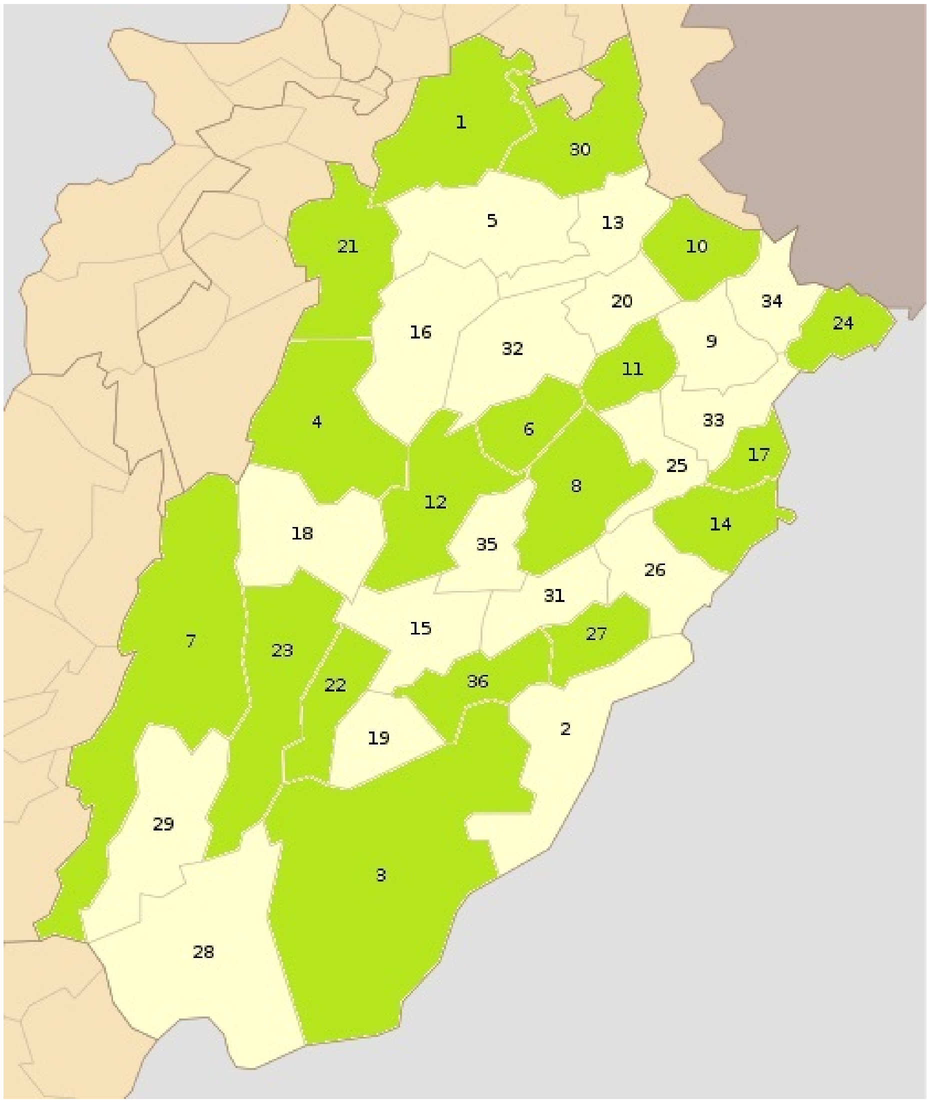


Figure 3: Treatment and Control Districts

inspectors in a district are required to attend monthly meetings. While they typically have frequent interactions within districts, these relations are much weaker across districts.

4 Data

We collected primary data on a representative sample of BHUs 850 (34 percent) of the 2,496 Basic Health Units in Punjab. We visited these facilities three times, first in November 2011, then in June 2012 and in October 2012. BHUs were selected randomly using an Equal

Probability of Selection (EPS) design, stratified on district and distance between the district headquarters and the BHU. Therefore, our estimates of absence are self-weighting, and so no sampling corrections are used in the analysis. All districts in Punjab except Khanewal are represented in our data. To our knowledge, this is the first representative survey of BHUs in Punjab. Figure 4 provides a map of the Basic Health Units in our experimental sample along with the different Provincial Assembly constituencies in Punjab.

In our sample of 850 clinics, we collected data through independent inspection. Our team collected information on staff absence and facility usage. Our staff interviewed the Medical Officer, the Dispenser or Health/Medical Technician, and the Lady Health Visitor before physically verifying the attendence of the Mid-Wife and the School Health and Nutrition Specialist. The attendance sheet for the staff was filled out at the end of the interviews and in private. Data collection and entry followed backchecks and other validation processes consistent with academic best practice.

Our survey teams were trained at regional hubs (four in total) where they were trained by senior enumerator trainers and our team members. Following these trainings, the teams made visits to BHUs in their assigned districts and remained in regular contact with their team leaders and our research team. Surveys took three weeks to field for each wave.

5 Elections and Health Worker Attendance

To motivate our analysis, we present a few correlations which suggest a relationship between the strength of local politicians and doctor attendance. During our doctor interviews, we collected data on their tenure in the post, the distance of their post from their hometown, and whether they know the local Member of the Provincial Assembly (MPA) personally. To ensure sampling of doctors who were not present at their clinics during any of our three visits, we pursued the absent doctors until we could find them and interview them. For this analysis, we restrict ourselves to control districts to avoid reporting correlations induced by

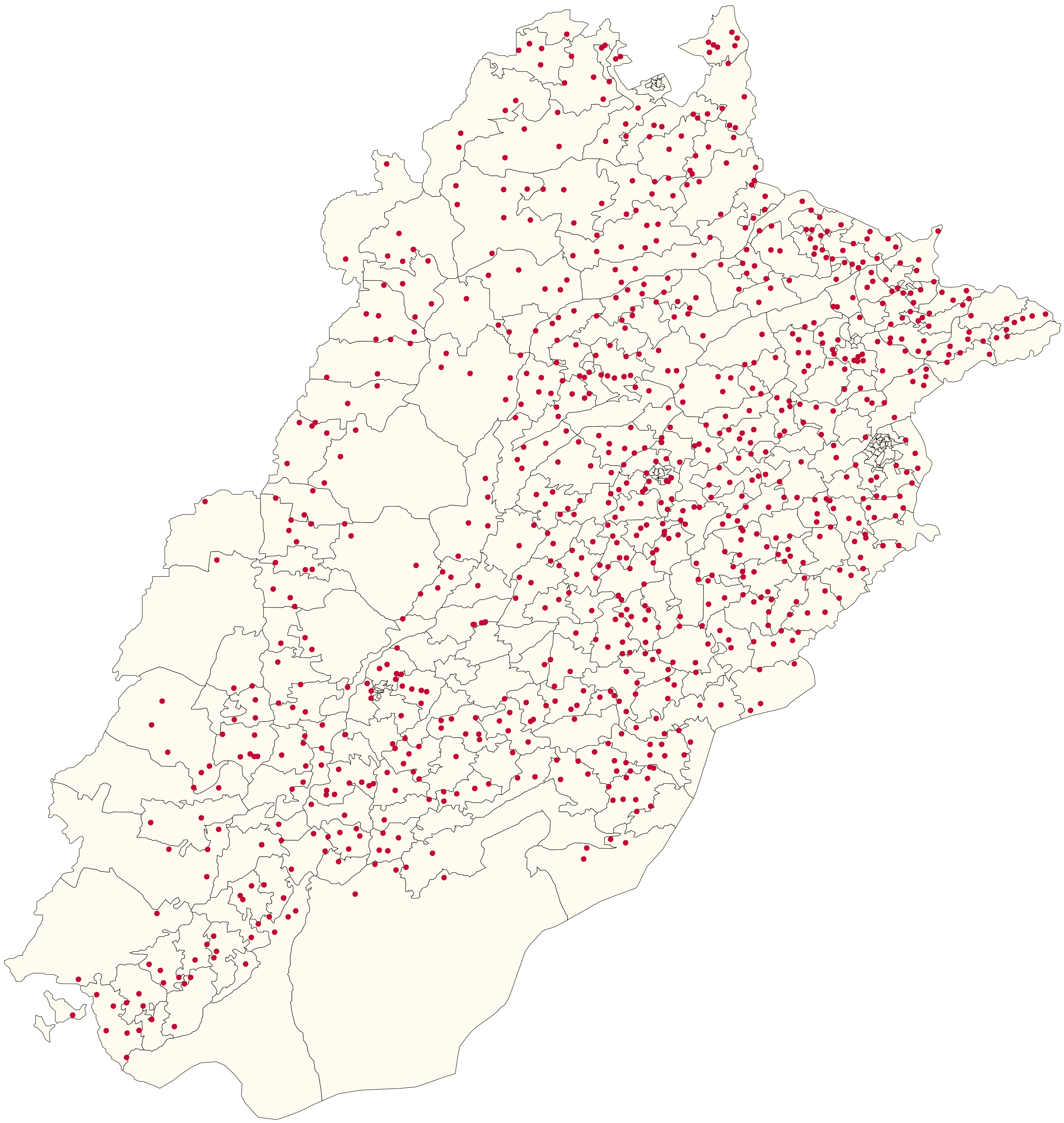


Figure 4: Locations of Basic Health Units in the Experimental Sample

our treatment.

Table 1 summarizes the data used for this analysis. The data reveal that doctor attendance in our control districts is quite low. While our visits took place during normal operating hours, we were able to locate doctors in only 22.5 percent of our visits. All BHUs are supposed to have doctors posted. However, because of a combination of a shortage of doctors, a lack of interest in rural postings, and perhaps misreporting to disguise absence, we find that only 53.2 percent of BHUs have doctors posted. Even accounting for this low rate of posting, doctor are present at only 42.29 percent of actual postings. Of the set of doctors we observe, 24 percent report knowing the doctor personally.

Table 1: Summary Statistics

Variable	Mean	Standard Deviation	# Observations
Doctor Present (=1)	0.225	0.418	1192
Doctor Posted at Clinic (=1)	0.532	0.499	1192
Doctor Knows Local MPA Personally (=1)	0.24	0.428	569
Distance to Doctor's Hometown (km)	122.765	302.062	204
Doctor's Months of Service	98.872	98.769	195
Distance to District Headquarters (km)	49.065	28.781	1258
Catchment Population (1,000)	24.777	8.547	1249
Political Concentration	0.62	0.139	1259
Victory Margin Share	0.157	0.106	1259

Notes: Sample: Control district clinics, survey waves 1 - 3. Political Concentration is a Herfindahl index computed as the sum of squared vote shares for each party in a Provincial Assembly constituency ranging from 0.19 in the most competitive district to one in uncontested districts.

As we describe in Section 4, we identified the provincial assembly constituency in which each of our clinics are located. In our control districts, we have BHUs in 124 constituencies. We construct two measures of the degree of local electoral capture: "political concentration," a normalized Herfindahl index computed as the sum of squared vote shares for each party in the constituency divided by the maximum Herfindahl score in our sample (0.55) and "Victory Margin Share" which is simply the victory margin for the winning candidate as a share of total votes cast in the local election. Political concentration ranges from 0.325 in the most competitive constituency to one in uncontested constituencies.[9] The victory margin share in these 124 constituencies ranges from 0.0016 percent to 1 in uncontested districts. Figure 5 maps the political concentration measure for each constituency in Punjab. The degree of political contestation appears only weakly correlated with geography.

In Table 2 we report correlations between these measures of local political competition and doctor attendance. Columns (1) - (3) report regressions using the political concentration Herfindahl as an explanatory variable and (4) - (6) report the same specifications using victory margin share. We find that doctors attend work more often in competitive constituencies. In all specifications, we include Tehsil (county) fixed effects, which restricts our variation to geographically proximate political constituencies that should be broadly similar in terms of remoteness, climate, and desirability of doctor postings. While there are a range of plausible omitted variables prohibiting a causal interpretation, we find that the correlation is robust to including controls for catchment population, distance to the district center, and whether a doctor was reported by other staff to be posted.

The results in Table 2 are consistent with two theories. First, it may be that in highly competitive districts politicians face stronger incentives to make sure health services are effectively delivered. Second, it may be that politicians who can capture districts are more likely to provide sinecures as patronage. Doctors in patronage jobs may be expected to work less. To investigate which of these is operative, we asked doctors whether they knew their local MPA personally. 266 doctors were absent during all of our three visits. After our third visit to the facilities, we pursued all 266 until we were able to interview them.

Table 3 examines whether doctors with a direct connection to the provincial assembly member serving in their constituency are more likely to be absent. We run regressions of the form:

$$Present_i = \beta_0 + \beta_1 Knows\ Parliamentarian_i + \epsilon_i \tag{1}$$

[9]Before dividing by the maximum Herfindahl score in our sample, political concentration ranges from 0.19 to 0.55

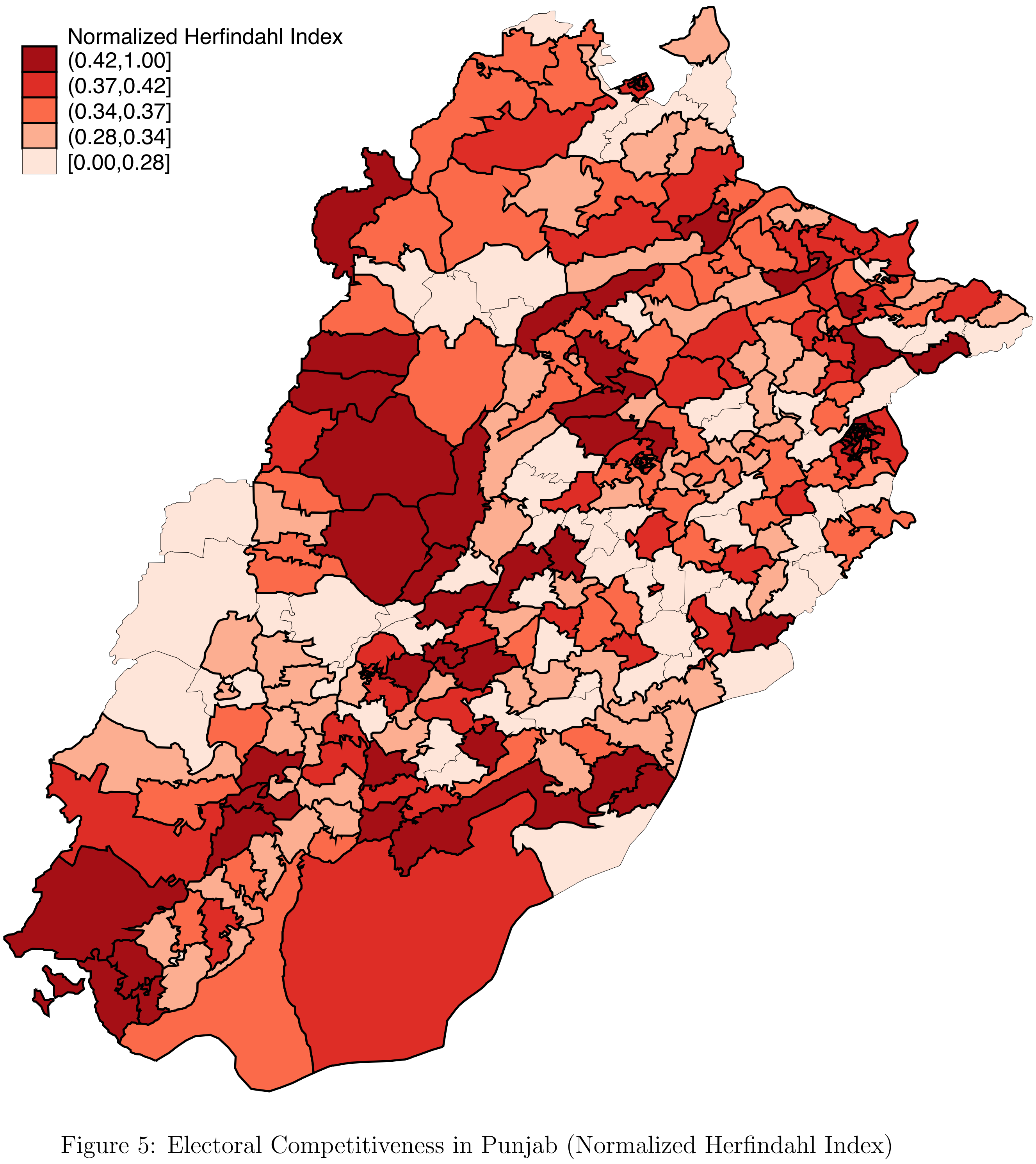


Figure 5: Electoral Competitiveness in Punjab (Normalized Herfindahl Index)

Table 2: Political Competition and Doctor Attendance

Dependent Variable:	Doctor Present (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Political Concentration	-0.374***	-0.354**	-0.176*			
	(0.135)	(0.136)	(0.097)			
Victory Margin				-0.265	-0.297*	-0.224*
				(0.178)	(0.166)	(0.120)
Distance to District Center (km)		-0.002***	-0.001*		-0.003***	-0.001**
		(0.001)	(0.001)		(0.001)	(0.001)
Catchment Population (1,000)		0.004*	0.001		0.004**	0.001
		(0.002)	(0.002)		(0.002)	(0.002)
Doctor Assigned (=1)			0.403***			0.405***
			(0.031)			(0.031)
Constant	0.465***	0.488***	0.140*	0.275***	0.306***	0.060
	(0.086)	(0.111)	(0.082)	(0.029)	(0.058)	(0.048)
# Constituences	124	124	124	124	124	124
# Observations	1190	1182	1182	1190	1182	1182
R-Squared	0.158	0.170	0.322	0.154	0.167	0.322

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Sample: Control district clinics survey waves 1 - 3. Standard errors clustered at the provincial assembly constituency level reported in parentheses. Sample: control district Basic Health Units (BHUs). Political Concentration is a Herfindahl index computed as the sum of squared vote shares for each party in a constituency ranging from 0.19 in the most competitive district to 1 in uncontested districts. All regressions include Tehsil (county) and survey wave fixed effects.

for each doctor i in our sample. We record whether doctors are present on three separate visits. $Present_i$ therefore ranges between 0 and 3.

Columns (1) - (4) report results using only the 188 doctors posted in our control sample. Column(5) reports the same specification for our entire sample. Doctors who do not know their local MPA directly are present at an average of 1.237 of our 3 visits, while doctors who do know their MPA are present at only 0.727 visits. These effects are robust to including either district or Tehsil fixed effects, and including a range of controls. We provide further support for the arguments that connected doctors enjoy preferential benefits in Table A1. We find that doctors who know their local MPA are able to obtain postings closer to their hometown, which are widely thought to be more desirable.

These correlations suggest that local politicians may secure office by providing sinecures to supporters. This theory has predictions for the effectiveness of our experiment. Politically connected inspectors and doctors should be less sensitive to monitoring. While monitoring innovations increase the probability they are detected shirking, these incentives will not be

Table 3: Political Connections and Doctor Attendance

Dependent Variable:	Number of Times Doctor Present (Max = 3)				
	(1)	(2)	(3)	(4)	(5)
Doctor Knows Local MPA Personally (=1)	-0.510***	-0.497***	-0.356**	-0.462**	-0.351***
	(0.133)	(0.143)	(0.158)	(0.178)	(0.123)
Patients Treated		0.000	-0.000	-0.000	0.000*
		(0.000)	(0.000)	(0.000)	(0.000)
Catchment Population (1,000)		-0.002	0.001	-0.005	-0.001
		(0.007)	(0.007)	(0.008)	(0.004)
Distance to District Center (km)		0.004*	0.000	-0.003	-0.003
		(0.002)	(0.003)	(0.003)	(0.002)
Doctor Assigned (=1)		0.757***	0.630**	0.582*	0.954***
		(0.230)	(0.262)	(0.330)	(0.207)
Constant	1.237***	0.372	0.668**	1.013***	0.469*
	(0.065)	(0.279)	(0.320)	(0.377)	(0.247)
# Observations	189	188	188	188	433
R-Squared	0.057	0.112	0.223	0.383	0.435
District Fixed Effects	No	No	Yes	No	No
Tehsil (County) Fixed Effects	No	No	No	Yes	Yes
Sample	Controls	Controls	Controls	Controls	Full Sample

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Robust standard errors reported in parentheses. Sample: control district Basic Health Units (BHUs). Political Concentration is a Herfindahl index computed as the sum of squared vote shares for each party in a constituency ranging from 0.19 in the most competitive district to 1 in uncontested districts. All regressions include Tehsil (county) and survey wave fixed effects.

binding for bureaucrats who are protected by their relations to local politicians.

6 Experimental Results

With this motivation as background, we now present our experimental results. Table 4 verifies balance in our experiment. As we discuss in Section 3, we stratified treatment on the share of staff present during our baseline interview. While this achieved balance for five of the six categories of staff that are supposed to be present at BHUs, we have a large and significant imbalance for doctors. Figure A1 reports a long time series of administrative data on doctor attendance. We find that the difference in levels does not reflect a difference in pre-treatment trends, allaying concerns that our fixed effects estimates are not causal.[10]

We begin by examining the impact of treatment on health worker attendance. We test

[10]Note that this depicts the sample average. The effects we find on doctor attendance are localized to the subsample of clinics in competitive districts.

Table 4: Randomization Verification

	Conventional Monitoring (=1)	Smartphone Monitoring (=1)	Difference	P-value
BHU open during visit (=1)	0.926	0.930	-0.003	0.915
	[0.261]	[0.256]	(0.031)	
Inspector Has Visited in the Last Month (=1)	0.234	0.214	0.020	0.731
	[0.424]	[0.411]	(0.057)	
Number of Staff Present	2.729	2.874	-0.144	0.431
	[1.514]	[1.638]	(0.181)	
Number of Staff Assigned	5.121	5.286	-0.165	0.199
	[0.924]	[0.941]	(0.126)	
Medical Officer Present (=1)	0.234	0.412	-0.177	0.003
	[0.424]	[0.493]	(0.055)	
Health Technician Present (=1)	0.398	0.347	0.050	0.379
	[0.490]	[0.477]	(0.057)	
Dispenser Present (=1)	0.707	0.777	-0.070	0.277
	[0.456]	[0.417]	(0.063)	
SHNS Present (=1)	0.348	0.340	0.008	0.890
	[0.477]	[0.474]	(0.059)	
Lady Health Visitor Present (=1)	0.587	0.629	-0.042	0.422
	[0.493]	[0.484]	(0.052)	
Midwife Present (=1)	0.538	0.474	0.064	0.164
	[0.499]	[0.500]	(0.045)	
Political Concentration Herfindahl	0.620	0.615	0.005	0.825
	0.139	0.132	0.022	
# of Observations	421	427		

Notes: *Level of significance*: Variable standard deviations reported in brackets. Standard errors clustered at the district level reported in parentheses.

for impacts on inspectors, where the program provides the sharpest incentives, doctors, and total staff.

We estimate regressions of the form:

$$Y_{dit} = \alpha + \beta Treatment_{dit} + \sum_{i=1}^{3} \delta_t + \lambda_i + \varepsilon_{it} \tag{2}$$

Y_{dit} is health worker attendance or official inspection, where i refers to the clinic, d refers to the district, and t to the survey wave. We cluster all standard errors at the district level. With only 35 districts, we also use randomization inference. Figure 8 shows our actual impact against impacts estimated from 1,000 hypothetical treatment assignments.

The first column verifies that the program increased inspections. The smartphone monitoring system directly impacts health inspectors, as their activities are geostamped, timestamped, and observed in real time. We do not observe any significant average impacts on

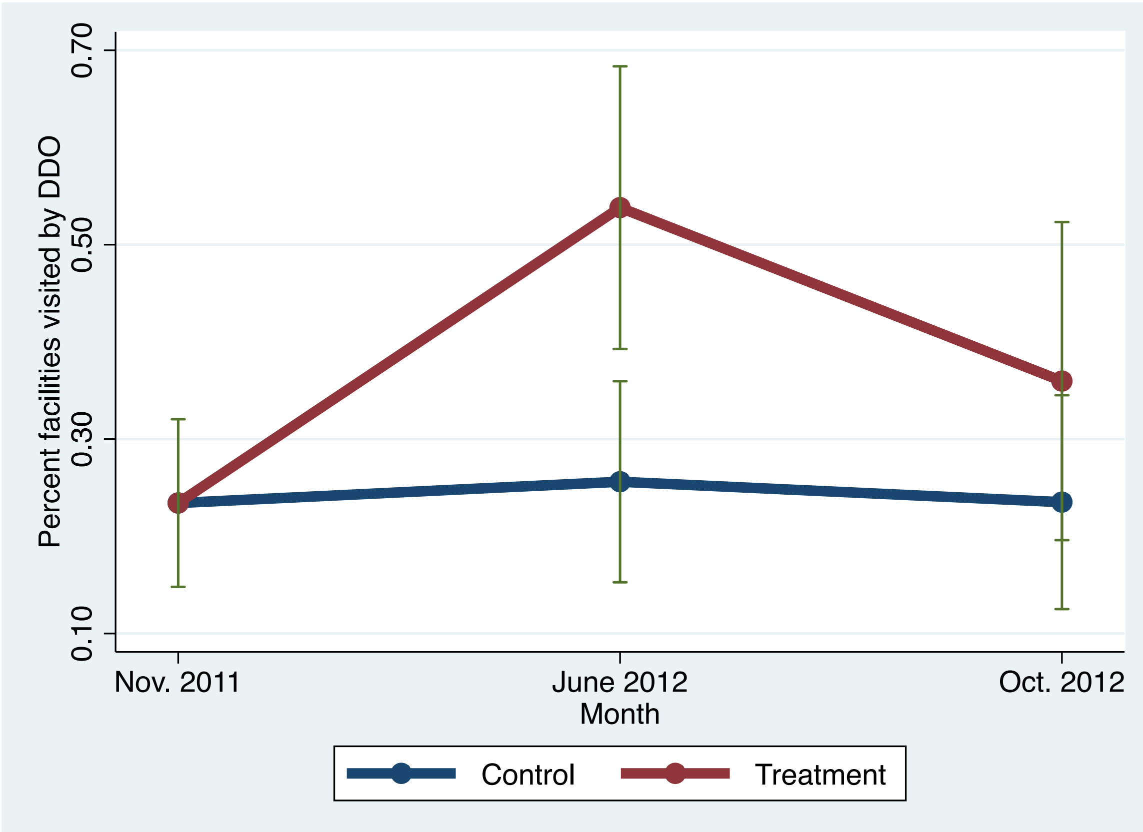


Figure 6: Effects by Survey Wave

doctor or overall staff attendance.

Panel B reports results splitting the treatment by survey wave 2 (May 2012) and wave 3 (October 2012). In column one, we see that the large impact on inspection has attenuated somewhat over the life of the program. Inspections remain 89% higher than they were at baseline. Figure 6 depicts attendance in treatment and control groups by wave. Future data collection will indicate whether this downward trend sustains. In columns (2) - (5), we again see no evidence of impact.

The correlations we find in Section 5 above suggest the possibility of heterogeneity by the degree of political concentration. Popular accounts of local politics in Pakistan characterize it broadly as a clientelistic system—a view strongly supported by our interviews with a select group of experienced parliamentarians. Parliamentarians can influence both the allocation of public sector jobs, and the enforcement of reporting requirements. We use the large degree of

Table 5: Impact on Inspections and Health Worker Attendance

Panel A - Average Effects	Inspected (=1)	Number of Staff Present		Doctor Present (=1)	
	(1)	(2)	(3)	(4)	(5)
Smartphone Monitoring (=1)	0.220***	-0.022	0.034	-0.016	-0.024
	(0.062)	(0.230)	(0.201)	(0.044)	(0.038)
# Staff Assigned			0.435***		
			(0.039)		
Doctor Assigned (=1)					0.368***
					(0.035)
Constant	0.217***	2.803***	0.538**	0.326***	0.087***
	(0.022)	(0.076)	(0.213)	(0.015)	(0.028)
# Districts	35	35	35	35	35
# Clinics	838	848	848	848	848
# Observations	2167	2542	2542	2414	2414
R-Squared	0.054	0.007	0.140	0.005	0.107

Panel B - Effects By Survey Wave	Inspected (=1)	Number of Staff Present		Doctor Present (=1)	
	(1)	(2)	(3)	(4)	(5)
Monitoring x Wave 2	0.300***	-0.144	-0.063	-0.035	-0.036
	(0.076)	(0.251)	(0.216)	(0.056)	(0.050)
Monitoring x Wave 3	0.146*	0.098	0.131	0.002	-0.013
	(0.079)	(0.245)	(0.216)	(0.054)	(0.048)
# Staff Assigned			0.434***		
			(0.038)		
Doctor Assigned (=1)					0.367***
					(0.035)
Constant	0.217***	2.803***	0.544**	0.326***	0.087***
	(0.022)	(0.076)	(0.209)	(0.015)	(0.028)
# Districts	35	35	35	35	35
# Clinics	838	848	848	848	848
# Observations	2167	2542	2542	2414	2414
R-Squared	0.063	0.009	0.141	0.006	0.107

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the district level reported in parentheses. All regressions include clinic and survey wave fixed effects.

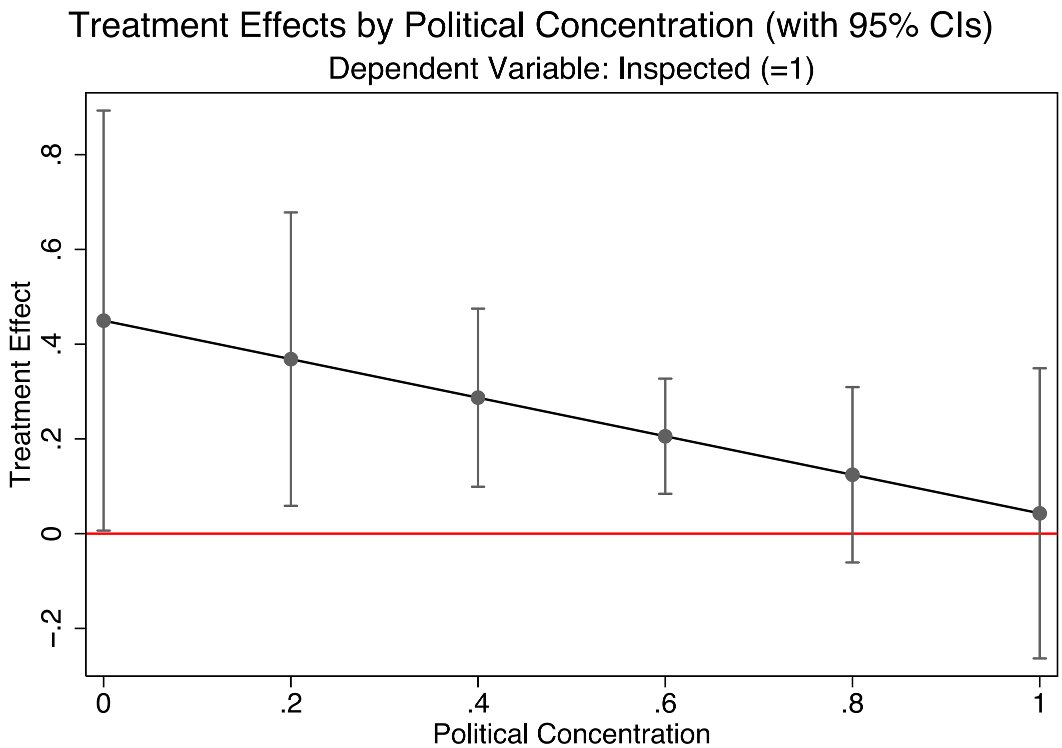
variation in competitiveness across the 241 constituencies in our sample to check for impact heterogeneity.

Table 6: Treatment Effects by Political Concentration

Dependent Var.	Inspected (=1)	Number of Staff Present		Doctor Present (=1)	
	(1)	(2)	(3)	(4)	(5)
Smartphone Monitoring (=1)	0.519**	1.390*	1.664**	0.321*	0.291*
	(0.225)	(0.717)	(0.736)	(0.180)	(0.163)
Monitoring x Political Concentration	-0.485	-2.254*	-2.626**	-0.547**	-0.514**
	(0.360)	(1.265)	(1.207)	(0.264)	(0.239)
# Staff Assigned			0.434***		
			(0.035)		
Doctor Assigned (=1)					0.368***
					(0.036)
Constant	0.217***	2.804***	0.545***	0.327***	0.087***
	(0.022)	(0.074)	(0.195)	(0.014)	(0.028)
# Districts	35	35	35	35	35
# Clinics	836	845	845	845	845
# Observations	2164	2534	2534	2410	2410
R-Squared	0.056	0.014	0.144	0.009	0.110

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the district level reported in parentheses. All regressions include clinic and survey wave fixed effects.

Consistent with the correlations presented in Section 5, we find that monitoring leads to a larger increase in attendance in competitive districts. The first column of Table 6 indicates that our increase in monitoring is localized to competitive constituencies. Similarly, in columns (2) and (3), we find that treatment results in roughly an additional worker being present in the most competitive districts. Last, in columns (4) and (5) we find that doctors are present at about 30 percent more facilities in competitive constituencies, with no effect in noncompetitive constituencies.



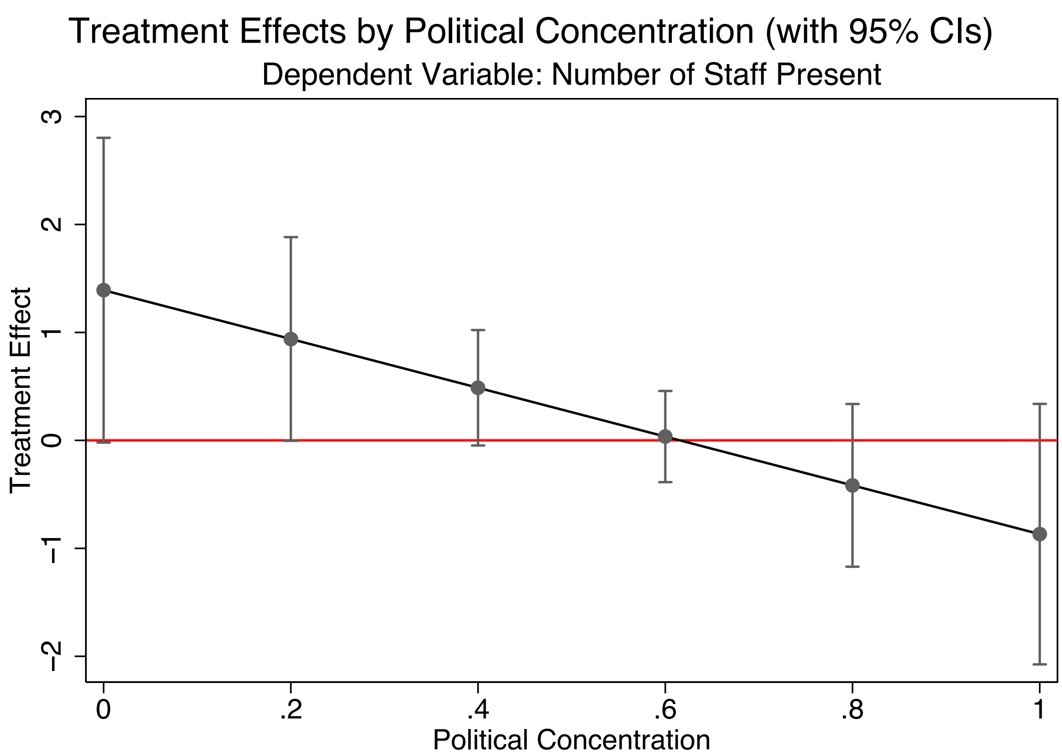


Figure 7: Treatment Effects by Political Concentration

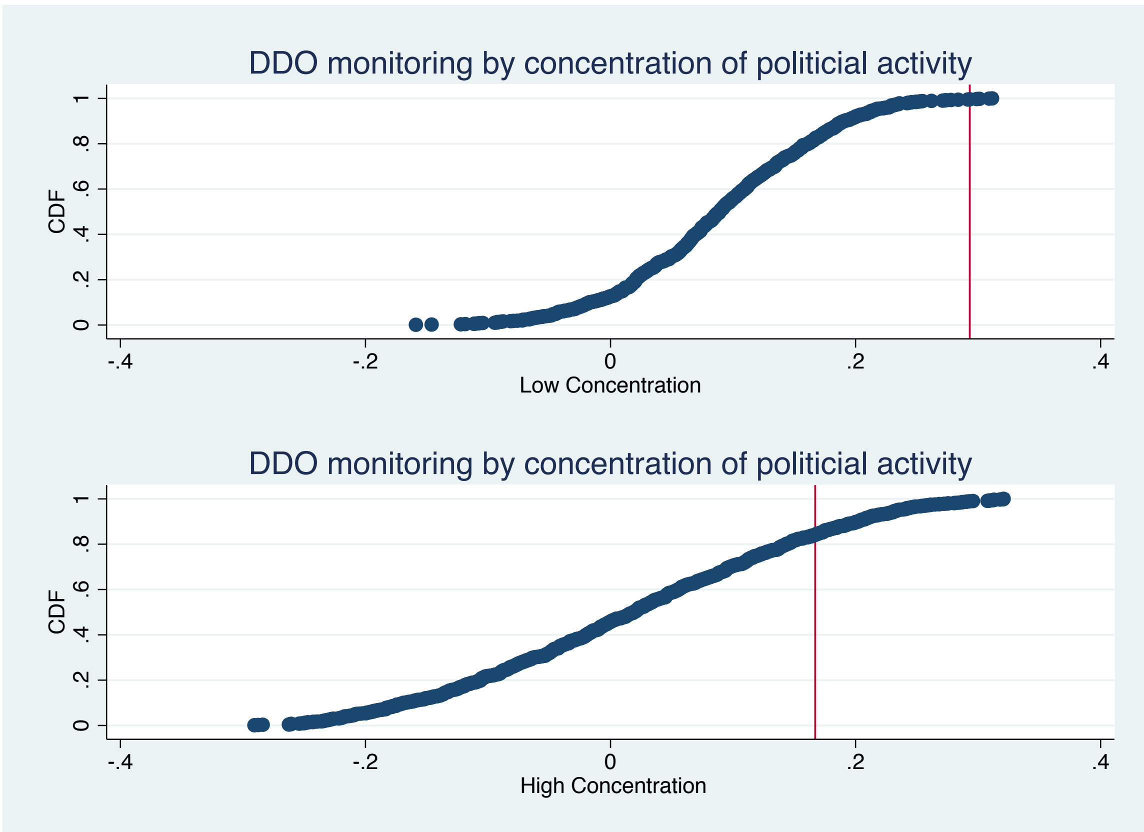


Figure 8: Estimated Distributions of Impacts by Political Concentration

7 Conclusion

In clientelistic systems, politicians gain office by providing targeted goods to supporters instead of by effectively providing public goods. We examine a particular case: doctors may be absent and unavailable to provide health care because their position is a sinecure provided in return for political support. Three findings support this explanation for public worker absence. First, absence is significantly more severe in less competitive districts. Second, politically connected workers are absent more frequently. Third, the effects of a novel monitoring regime on the performance of government monitors remain localized to competitive districts.

Doctor, teacher, and other public worker absence is a serious obstacle to effective public service delivery in developing countries (Banerjee and Duflo 2006; Chaudhury et al. 2006). In many cases, it is also highly resistant to interventions aimed to promote attendance. Understanding the political rationale for public worker absence opens a broader set of interventions to combat the problem. First, increasing voters awareness of public worker absence might amplify the political costs from voters not motivated by patronage.[11] Additionally, professionalizing the civil service, and eliminating politicians involvement in decisions related to bureaucratic hiring, firing, promotion, and posting would remove the opportunity to use these positions as patronage.

More generally, anti-corruption efforts are rarely successful. Our findings suggest that in some cases the resilience of public sector corruption may be because it is maintained for reasons of political expedience. Given the huge potential payouts to politicians from facilitating corruption, future research in the economics of corruption should consider the political rationale for corruption. Such investigations could broaden the set of anti-corruption policies and substantially increase their impact.

[11] Along these lines, Wilson (1961) states "organized guardians of the civic purse will not permit corrupt politicoans to increase city expenditures through certain kinds of projects (for example, urban renewal, street-lighting, street-cleaning, building inspection, fire and police protection) but not through others (increasing the staffs of aldermen, multiplying executive secretariats, and hiring men to do jobs which machines can do better—such as operating elevators, sweeping streets, etc.)"

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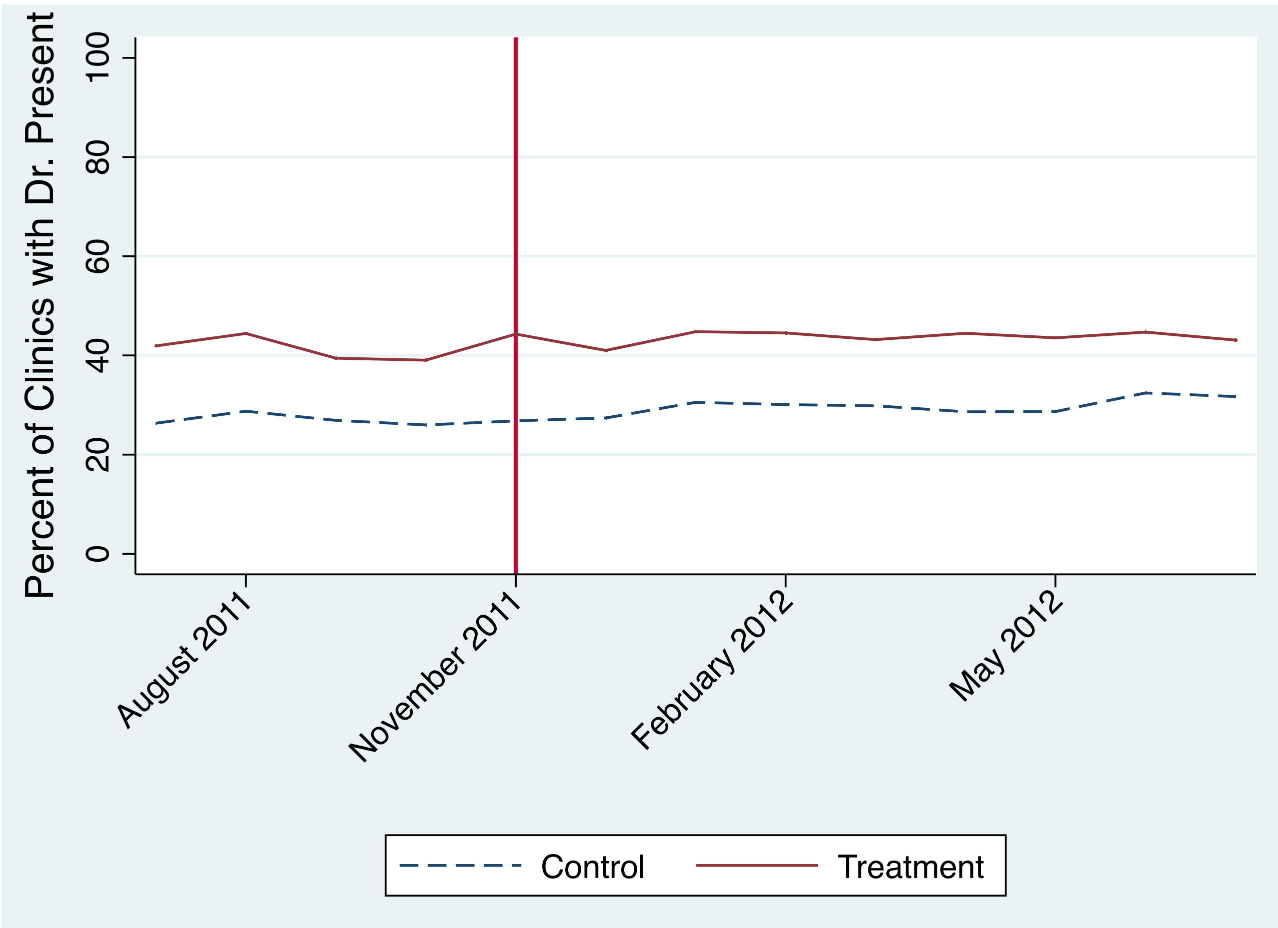

Figure A1: Average Doctor Attendance Before and After Treatment

Table A1: Connections and Perks

Dependent Variable:	Distance to Doctor's Hometown (km)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Doctor Knows MP Personally (=1)	-131.628***	-112.918***	-127.607***	-95.366**	-270.811***	-314.565	-393.636*
	(35.431)	(35.675)	(41.792)	(46.485)	(83.030)	(188.270)	(212.932)
Doctor's Years of Service			0.093	0.035			1.977
			(0.307)	(0.361)			(1.578)
Catchment Population (1,000)			-1.950	-1.417			-5.550
			(2.579)	(2.471)			(11.668)
Distance to District Center (km)			1.066	2.023			0.995
			(0.899)	(1.240)			(4.310)
Constant	198.698***	185.783***	191.748**	126.098	449.808***	460.512***	444.783
	(47.187)	(42.578)	(95.577)	(90.661)	(105.185)	(99.948)	(364.098)
District Fixed Effects	No	Yes	Yes	No	No	Yes	Yes
Tehsil (County) Fixed Effects	No	No	No	Yes	No	No	No
Sample	Full	Full	Full	Full	>50km	>50km	>50km
# Observations	204	204	194	194	60	60	56
R-Squared	0.045	0.214	0.233	0.385	0.063	0.429	0.494

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors clustered at the Basic Health Unit (BHU) level reported in parentheses. Sample: Full - control district BHUs; >50km - control BHUs where doctor is further than 50km from their hometown. All regressions include Tehsil (county) and survey wave fixed effects.