14.770: Corruption Lecture 24-27c

Ben Olken

Outline

- Do we care?
 - Magnitude and efficiency costs
- The corrupt official's decision problem
 - Balancing risks, rents, and incentives
- Embedding corruption into larger structures
 - The IO of corruption: embedding the decision problem into a market structure
 - Corruption and politics
 - Corruption's general equilibrium effects on the economy

Industrial Organization of Corruption

Shleifer and Vishny (1993): Corruption

- Shleifer and Vishny (1993):
 - Key idea: think of bribe as a price, which is set endogenously to maximize profits
 - Analogy is to a monopolist
- Two types of corruption:
 - Corruption without theft bribes paid on top of official fees
 - Corruption decreases efficiency
 - Orruption with theft bribes paid instead of fees
 - Aligns the interests of briber and bribe payer and sustains corruption
 - Efficiency implications unclear

Corruption without theft



Corruption without Theft

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Corruption with theft



FIGURE Ib Corruption with Theft

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Centralized vs. decentralized corruption

- Idea: Corruption was more efficient in Communist Russia than in post-Communist Russia, or under Soeharto in Indonesia than in Indonesia today
- Suppose you need *n* permits to build a house
- Building a house has value v. Distribution of v determines demand q(P), elasticity $\varepsilon(P)$
- Decentralized bribe-setting:
 - Each official announced a fixed price p_i . Define $P = \sum p_j$
 - Each official maximizes

$$p_i q \quad p_i + \sum_{j \neq i} p_j \bigg) \bigg($$

• In equilibrium, we obtain a standard double-marginzaliation result:

$$\frac{q'(P)P}{q(P)} = -n$$

Centralized vs. decentralized corruption

• Predictions:

$$If \varepsilon'(P) < 0, then \frac{\partial P}{\partial n} > 0$$

• Note that $\varepsilon'\left(P\right)<0$ required to generate finite price in monopoly model with 0 marginal cost

2 If
$$q(P)$$
 not "too convex", then $\frac{\partial \frac{P}{n}}{\partial n} < 0$

• Sufficient condition is that
$$rac{q''(P)P}{q'(P)}>-1$$
, or $q''\leq 0$

Alternative models:

• If pricing was centralized, then:

•
$$\varepsilon(P) = -1$$
 in equilibrium
• $\frac{\partial P}{\partial n} = 0$

• If pricing was exogenous, then

•
$$\frac{\partial \frac{P}{n}}{\partial n} = 0$$

Competition

- Now suppose permits are perfect substitutes, i.e., you can get the permit either from agent 1 or agent 2.
 - If agents engage in Bertrand competition, then bribes are driven down to 0.
 - If agents engage in Cournot competition, then $\frac{\partial p}{\partial n} < 0$

Empirical Test: Trucking in Aceh

Olken and Barron (2009): The Simple Economics of Extortion: Evidence from Trucking in Aceh

- Setting: long-distance trucking in Aceh, Indonesia
- In addition to weigh stations (which we discussed before), trucks stop and pay bribes at checkpoints along the route
 - Set up by police, military ostensibly for security reasons, but mostly now for rent extraction
 - Drivers pay to avoid being harassed / ticketed by officers manning checkpoint
 - More like extortion than bribery: officer only mentioned a violation in 24 out of 5,387 transactions
 - Average payment: Rp. 5,000 Rp. 10,000 (US \$0.55 US \$1.10)
 - Average of 20 checkpoints per trip
- Idea: checkpoints are like a string of monopolists you need to pay all of them to complete a trip

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Figure 1: Routes



Empirical strategy: military withdrawal from Aceh

- Thirty-year conflict between Indonesian government and Acehenese rebels (GAM)
 - Peace agreement signed in August 2005 to withdraw 30,000 police and military in 4 phases from September 2005 January 2006
 - Data is from November 2005 June 2006, and so encompasses the 3rd and 4th withdrawal phases, as well as post-period
 - Most checkpoints in Aceh had already disappeared from Banda Aceh route by the time data, so focus on Meulaboh route
- Trips passed through two provinces (Aceh and North Sumatra), but military withdrawals did not affect North Sumatra province
- Empirical strategy:
 - Withdrawal on troops from portion of Meulaboh-Medan route in Aceh province reduced number of checkpoints on the route (n)
 - Assumption: no direct effect of withdrawal on checkpoints in North Sumatra province
 - Therefore, can use changes in prices charged at checkpoints in North Sumatra to identify $\frac{\partial \frac{\rho}{n}}{\partial n}$ from the Shlieifer-Vishny model

Data

- Direct observation of 304 trips across the two routes
 - Locally-recruited enumerators accompanied drivers on their regular routes, writing down all payments
 - Dressed as (and fulfilling role of) truck drivers' assistants
 - Total of over 6,000 illegal payments
- On average, extortion / bribes / protection payments are about 13% of cost of trip – more than drivers' salary
- Video

Impact of withdrawal of posts on bribes

• Estimation 1: Checkpoint level, with all checkpoints on Meulaboh -Medan road *in North Sumatra province*

 $LOGPRICE_{ci} = \alpha_c + X'_i \gamma + \beta LOGEXPECTEDPOSTS_i + \varepsilon_{ci}$

- Includes checkpoint fixed effects (α_c)
- LOGEXPECTEDPOSTS_i isolates variation from change in Aceh posts.
- Can add Banda Aceh trips as a control group
- Predictions:
 - Note that $LOGPRICE_{ci} = LOG(P) LOG(n)$
 - Centralized model: $\beta = -1$
 - Decentralized model: $-1 < \beta < 0$
 - "Exogenous" pricing model: $\beta = 0$

Impact of withdrawal of posts on bribes

• Estimation 2: Time series of total payments in North Sumatra.

 $LOGPAYMENT_i = \alpha + X'_i \gamma + \beta LOGEXPECTEDPOSTS_i + \varepsilon_i$

- LOGPAYMENT; is total payments in North Sumatra Province
- Includes weigh stations, allows us to account for potentially endogenous changes in number of checkpoints
- Can continue to use Banda Aceh road as control group
- Convincing?
- Main threat to identification is differential time trends between routes

Results

Figure 3: Impact of troop withdrawals



Meulaboh





Banda Aceh



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Results

ECONOMICS OF EXTORTION

IMPLE 2 IMPACT OF NUMBER OF CHECKPOINTS IN ACEH ON BRIBES IN NORTH SUMATRA							
	Meulaboh OLS (1)	Meulaboh OLS (2)	Meulaboh (Pre-Press Conference) OLS (3)	Meulaboh IV (4)	Both Routes OLS (5)	Both Routes OLS (6)	
	A. Log Payment at Checkpoint						
Log expected checkpoints on route	545*** (.157)	580*** (.167)	684*** (.257)	788*** (.217)	701*** (.202)	787*** (.203)	
Truck controls	No	Yes	Yes	Yes	Yes	Yes	
Common time effects	None	None	None	None	Cubic	Month FE	
Observations Test elasticity	1,941	1,720	1,069	1,720	2,369	2,369	
= 0	.00	.00	.01	.00	.00	.00	
Test elasticity = -1	.00	.01	.22	.33	.14	.29	

TABLE 9

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Does competition increase quantities and decrease bribes?

- With Cournot competition, as you increase the number of firms, quantities increase and prices decrease.
- Example from forestry:
 - Each district head can allow illegal logging in return for a bribe
 - As we increase the number of districts, total logging should increase and prices should fall
- Empirical setting:
 - In Indonesia, number of districts almost doubled between 2000 and 2008, with districts splits occurring asynchronously
 - We examine the impact of increasing number of districts in a market over time
- Tests:
 - Show impact on quantity using satellite data
 - Demonstrate impact on prices from official production data
- Can rule out various alternative explanations (impacts on legal production, changes in enforcement, differential time trends)

We track illegal logging using satellite imagery.

- MODIS satellite gives daily images of world at 250m resolution
- We use MODIS to construct annual change layers for forests for all Indonesia
 - Aggregate daily images to monthly level to get clearest cloud-free image for each pixel
 - Use 7 MODIS bands at monthly level + 8-day MODIS land surface temperature product -> over 130 images for each pixel
 - Use Landsat training data to predict deforestation
 - Once coded as deforested, coded as deforested forever
- Since we have pixel level data, we can overlay with GIS information on the four (fixed) forest zones – production, conversion, conservation, protection ⇒ enables us to look directly at illegal logging



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Logging increases as number of jurisdictions increase.

 Estimate fixed-effects Poisson Quasi-Maximum Likelihood count model:

$\mathbf{E}\left(\textit{deforest}_{\textit{pit}}\right) = \mu_{\textit{pi}} \exp\left(\beta\textit{NumDistrictsInProv}_{\textit{pit}} + \eta_{\textit{it}}\right)$

	(1)	(2) Production/	(3) Conservation/	(4)	(5)	(6)	(7)
	All Forest	Conversion	Protection	Conversion	Production	Conservation	Protection
Panel A							
Number of districts in province	0.0385** (0.0160)	0.0443** (0.0179)	0.0472 (0.0331)	0.0387 (0.0305)	0.0535*** (0.0199)	0.0976** (0.0411)	0.00870 (0.0349)
Observations	608	296	312	128	168	144	168
Panel B: including lags							
Number of districts in province (sum of L0-L3)	0.0822***	0.0809***	0.101**	0.0850	0.0795***	0.151***	0.0513
	(0.0204)	(0.0193)	(0.0426)	(0.0594)	(0.0217)	(0.0575)	(0.0373)
Observations	608	296	312	128	168	144	168

TABLE IV IMPACT OF NUMBER OF DISTRICTS IN PROVINCE ON DEFORESTATION AS MEASURED WITH SATELLITE DATA

Notes: The forest data set has been constructed from MODIS satellite images, as described in Section III.C. The Production and Conversion zones are those in which legal logging can take place, while the Conservation and Production zones are those in which all logging is likely. And observation is a forest-none in a province and each province in a given year, where provinces are defined using the 2000 boundaries (21) provinces. The regressions induced province variable constants the number of district within each province in a given year, where provinces are defined using the 2000 boundaries (21) provinces. The regressions includes province are district within and the first three lags. Robust standard errors are clustered at the 1990 province boundaries (17 provinces) and reported in parentheses. *** significant at 0.01 level, ** significant at 0.05 level.

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Prices for wood fall as number of jurisdictions increase.

• Estimate:

$\log(y_{wipt}) = \beta NumDistrictsInProv_{pit} + \mu_{wpi} + \eta_{wit} + \varepsilon_{wipt},$

	(1)	(2)	(3)	(4)	(5)	(6)
	200	1-2007	200	1-2007	199	4-2007
All wood observations		Balanced panel of	of wood observations	All wood observations		
Variables	Log price	Log quantity	Log price	Log quantity	Log price	Log quantity
Panel A						
Number of districts in province	-0.017	0.084*	-0.019	0.103**	-0.024^{**}	0.080***
	(0.012)	(0.044)	(0.013)	(0.039)	(0.010)	(0.017)
Observations	1003	1003	532	532	2355	2355
Panel B: including lags						
Number of districts in province	-0.0336^{**}	0.135^{**}	-0.0384^{**}	0.156^{**}	-0.0344^{**}	0.119^{***}
(sum of L0–L3)	(0.0134)	(0.0561)	(0.0150)	(0.0592)	(0.0139)	(0.0383)
Observations	1003	1003	532	532	1960	1960

TABLE V IMPACT OF NUMBER OF DISTRICTS IN PROVINCE ON PRICES AND QUANTITIES AS REPORTED BY OFFICIAL FOREST PRODUCTION STATISTICS

Notes: The price and quantity data has been compiled from the Statistics of Porest and Concession Estate, and are official government statistics for the Production zone only. The dependent variable in columns (1), (3), and (6) is the log price of a given wood type produced in the province-year, determined by dividing the total value of wood produced by the quantity and taking logs. The dependent variable in columns (2), (4), and (6) is the log guantity of a given wood type produced in the province part, and essential is a wood whose production is observed in all years for a given province, for the years 2001 to 2007, columns (5) and (6) is include all wood types, for the years 1904 to 2007. The number of districts in province variable counts the number of districts variable and three lags of the logs (2) provinces. In properties the second seco

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Magnitudes are consistent with benchmark Cournot model.

• Benchmark Cournot model:

$$\max_{q_i} q_i p\left(\sum q\right) \leftarrow cq_i$$

• Taking derivatives and rewriting yields: `

$$\frac{(p-c)}{p} = \frac{1}{n\varepsilon}$$

where n is number of jurisdictions and ε is elasticity of demand

• If we assume $p = \frac{a}{Q^{\lambda}}$, so we have constant elasticity of demand $\varepsilon = \frac{1}{\lambda}$, we can derive a formula for semi-elasticity of extraction with respect to n (which is what we estimate), i.e.

$$\frac{1}{Q}\frac{dQ}{dn} = \frac{1}{n^2 - n\lambda}$$

Magnitudes are results consistent with benchmark Cournot model.

- Does this match the data?
- With n = 5.5 and $\varepsilon = 2.1$, formula implies $\frac{1}{Q} \frac{dQ}{dn} = \frac{1}{n^2 n\lambda}$, which is about 0.035
- We estimate $\frac{1}{Q} \frac{dQ}{dn}$ to be between 0.036 in short run and 0.079 in long run so in the right order of magnitude

Transaction level IO issues

- Analysis above was about "market-level" IO issues
- There are also several important "transaction-level" IO issues
 - Bargaining and hold-up
 - Price discrimination
 - Auction design

Bargaining and hold-up

- Model above had fixed prices, announced in advance
- Suppose instead there was ex-post bargaining between the officer guarding the checkpoint and the truck driver
- Assume officer's bargaining weight α
- What happens at last checkpoint?
 - Officer receives α , driver keeps (1α)
- What happens at previous checkpoint?
 - Officer receives $\alpha (1 \alpha)$, driver keeps $1 \alpha (1 \alpha)$.
 - Why?
 - Intuition is that there is less surplus from agreement at "upstream" checkpoints, since some part of that surplus will be extracted at "downstream" checkpoints
 - Analogy is to ex-post bargaining in chain of Leontief production technologies (e.g. Blanchard and Kremer 1997)

Testing bargaining and hold-up

- First question: is there any ex-post bargaining?
- Certain factors likely to increase bargaining power of officer manning the post
 - Is officer carrying a gun?
 - How many officers are visible manning post?
- We can test whether these factors:
 - Increase amount paid at checkpoint
 - Increase probability of negotiation over amount paid
- Estimation:

 $LOGPRICE_{ci} = \alpha_i + \alpha_c + \beta_1 GUN_{ci} + \beta_2 NUMOFFICERS_{ci} + \varepsilon_{ci}$

• Includes trip fixed effects (α_i) and checkpoint \times month \times direction of travel fixed effects (α_c)

Results

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	Log Payment		Negotiate Dummy	
	(1)	(2)	(3)	(4)
Gun visible	.166**	.154**	.042**	.047***
	(.066)	(.070)	(.018)	(.018)
Gun visible at subsequent checkpoint	. ,	.016		.016
1 1		(.024)		(.018)
Number of officers at checkpoint	.047***	.050***	.017 * * *	.016***
1	(.010)	(.009)	(.004)	(.005)
Number of officers at subsequent	× ,	· /	· · /	. ,
checkpoint		003		003
1		(.007)		(.004)
Observations	5,260	4,968	5,281	4,989
Mean dependent variable	8.49	8.50	.13	.13

TABLE 4 BARGAINING VERSUS FIXED PRICES

NOTE. – This table presents the results from estimating eq. (8), where there is one observation for each payment at a checkpoint, and trip fixed effects and checkpoint v direction v month interval fixed effects are included. Robust standard errors are in parentheses, adjusted for clustering at the checkpoint level.

* Significant at 10 percent.

** Significant at 5 percent.

*** Significant at 1 percent.

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- Prediction from model: if α > 0, so there is some ex-post bargaining, prices increase as you near the end of the trip
- To estimate this, take advantage of the fact that we have trips in both directions
- For each checkpoint × direction of travel:
 - Define *MEANPERCENTILE_{ci}* as the percentile in the trip where the checkpoint is on average encountered each month
 - Each checkpoint will have two values of *MEANPERCENTILE_{ci}* each month, one going to Aceh and one coming from Aceh
- Estimation:

 $LOGPRICE_{ci} = \alpha_i + \alpha_c + \beta MEANPERCENTILE_{ci} + \varepsilon_{ci}$

• Includes trip fixed effects (α_i) and checkpoint \times month fixed effects (α_c)



FIG. 4.—Payments by percentile of trip. Each graph shows the results of a nonparametric

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TABLE 5 Sequential Bargaining and Increasing Prices

	Meulaboh (1)	Banda Aceh (2)
Mean percentile	.145***	178
Ĩ	(.045)	(.225)
Observations	4,190	1,089

Note.—This table presents the results from estimating eq. (9), where there is one observation for each payment at a checkpoint, and trip fixed effects and checkpoint × month interval fixed effects are included. Robust standard errors are in parentheses, adjusted for clustering at the checkpoint level.

* Significant at 10 percent.
** Significant at 5 percent.
*** Significant at 1 percent.

- Why Meulaboh but not Banda Aceh?
- Model predicts

$$\log b_n = -n\log\left(1-\alpha\right) + k$$

- Since we estimate the coefficient on $\frac{n}{N}$, $\beta = -N \log (1 \alpha)$
- Estimates from Meulaboh imply $\alpha = 0.005$
- Since there are fewer checkpoints on Banda Aceh route, the estimated slope β will be smaller
- Also, the presence of intermediate cities on the Banda Aceh route substantially weakens the prediction

Third degree price discrimination

- Theory: if corrupt officials can observe characteristics that are correlated with willingness to pay, they will adjust prices accordingly
- Estimation from trucking paper:

$$LOGPRICE_{ci} = \alpha_c + X'_i \beta + \varepsilon_{ci}$$

- Includes checkpoint \times month \times direction of travel fixed effects (α_c)
- Results indicate price discrimination on:
 - Truck age
 - Cargo value
 - Cargo types (higher for food, agricultural produce, steel)
- Svensson (2003) finds similar results in Uganda looking at firms' bribe payments

Third degree price discrimination

Do trucks with observable characteristics correlated with higher • willingness to pay in fact pay more?



FIG. 4.—Payments by percentile of trip. Each graph shows the results of a nonparametric © The University of Chicago Press. All rights reserved. This content is excluded from our Creative Commons license. For more information, see https://ocw.mit.edu/help/faq-fair-use/

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Second degree price discrimination

- Another type of price-discrimination is screening e.g., create different contracts and let people self-select
- Does this happen with corruption?
- Evidence
 - We saw evidence of this in the trucking paper at weigh stations
 - What else? Does drivers' license paper speak to this?

Procurement auctions

- Much corruption takes place in government procurement of goods and services
- To mitigate corruption (and other problems), governments typically procure through procurement auctions, which restrict the discretion that procurement officials have
- Procurement is more complicated than auctions to sell a product, since the procurer cares about quality in addition to price
- There are therefore two main types of procurement regimes:
 - Best-price auction: conditional on meeting a minimum quality threshold, lowest price wins
 - Best-value auctions: every bidder receives a quality score, and winner determined by a formula that combines quality and price
- Do these auctions prevent corruption? Under what circumstances? What auction rules work best for mitigating corruption?
- Tran (2008) finds that best-price auctions work, but best-value auctions actually make things worse. Why?

- Applying IO models to corruption: corrupt officials behave like firms in many ways
- Theory:
 - Market structure models (double marginalization, competition), with efficiency implications that depend on the context
 - Price discrimination as in standard IO contexts
- Empirics:
 - Evidence for double marginalization but no compelling evidence to date on competition
 - Evidence of price discrimination both third degree and (to a lesser degree) second degree
 - Evidence that auction design is important for corruption but this is an area for future work as well

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