SUPPLEMENTARY MATERIAL

LOCAL ORDER, POLICING, AND BRIBES Evidence from India

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Appendix

SURVEY

We use the following survey items in the analysis:

- Theft reporting: "Things get stolen from people's homes, and sometimes they go to the police and sometimes they do not. In which of the following situations would you go to the police? [select multiple]"
- Bribe cost: "How much do you think you would have to pay for the police to begin an investigation for the theft of X?"
- Police satisfaction: "How satisfied are you with the quality of LOCAL POLICING for your family?"
- Social connectedness:
 - "Suppose that 10 of your neighbors were invited to help in community work, such as a community water project, cleaning of gutters, or weeding on the side of the road. How many do you think would show up?"
 - "How often do people in your neighborhood help each other with problems (e.g. taking care of a sick family member, finding a job, lending money)?"
- Incidence of local conflict: "How often are there serious disagreements among people who live in this neighborhood?"
- Help from leader: "Did you receive help from neighborhood leader in dealing with: THEFT; POLICE;"

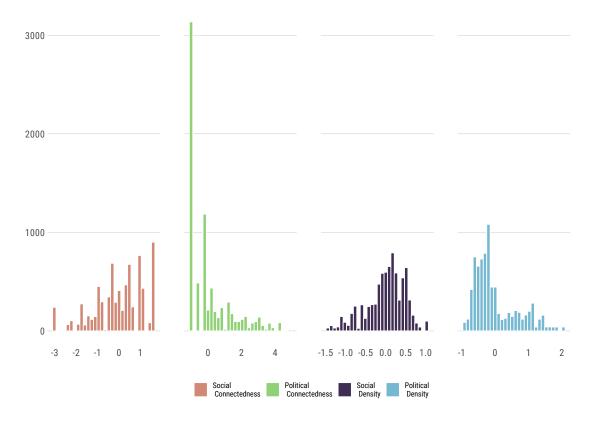
Assets. We follow prior approaches that measure economic well-being in the developing world by leveraging data on asset ownership (Deaton, 2006). We create indicators for whether the respondent owns a variety of assets and combine these into an index. We expect respondents with higher values on the index enjoy greater wealth than those

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with lower values on the index. The relevant assets include: small vehicles (i.e., motorcycle, rickshaw); sewing machines and other household tools; furniture; appliances such as fridges and stoves; communication appliances such as television, radio and cell phone; and whether the respondent owns any agricultural land.

Network Census. Data collection for the network census constituted a demanding survey and enumeration process. This proceeded as follows: first, enumerators collected a list of all residents in the slum, gathering the names of residents, and programming those names for subsequent use. With this list in place, enumerators then asked household respondents a set of 23 questions bearing on social, political and economic ties with individuals in their settlement; these questions asked respondents to provide the names of individuals they socialized with, talked politics with, would go to with problems, who helped them find jobs, etc.

This process resulted in 2581 respondents (one per household) in the 8 settlements and allows us to map their full social and political networks. To assess the relationship between our individual-connectedness questions and the social network density of respondents, we regress the network attributes of individuals, including their in-degree on responses to our individual connectedness measure.



Distribution of Connectedness and Density Variables

Figure A.1. Distribution of social and political connectedness, social and political slum density.

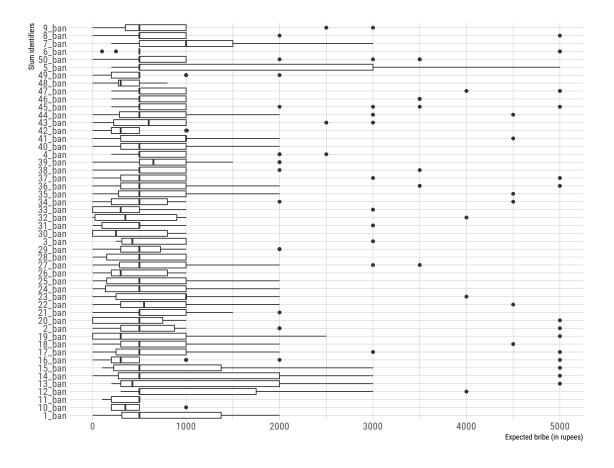


Figure A.2. Distribution of expected motorcycle theft bribe costs across neighborhoods.

	Social in-degree
Intercept	2.365***
-	(0.179)
Social Connectedness	0.144^{***}
	(0.048)
Age	0.004
	(0.004)
Gender	0.140
	(0.105)
Ν	2535
R-squared	0.006
Adj. R-squared	0.003
Residual Std. Error	$2.646 \; (df = 2527)$
F Statistic	2.051^{**} (df = 7; 2527)

Table A.1. Network model predicing social in-degree with social connectednessmeasure. Includes controls for religion and survey wave.

***p < .01; **p < .05; *p < .1

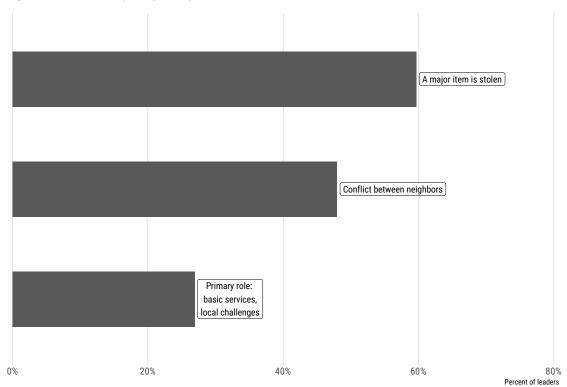
	Dependent variable:					
	Moto	TV	Stove	Moto	TV	Stove
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	$\begin{array}{c} 1.752^{***} \\ (0.521) \end{array}$	$\begin{array}{c} 0.864^{***} \\ (0.222) \end{array}$	-0.032 (0.342)	$\frac{1.970^{***}}{(0.558)}$	$\frac{1.022^{***}}{(0.232)}$	$0.148 \\ (0.347)$
Social connectedness	$\begin{array}{c} 0.371^{***} \\ (0.069) \end{array}$	$\begin{array}{c} 0.176^{***} \\ (0.033) \end{array}$	0.099^{**} (0.044)			
Social density	$\begin{array}{c} 0.222\\ (0.259) \end{array}$	$\begin{array}{c} 0.136 \\ (0.190) \end{array}$	$0.066 \\ (0.274)$			
Political connectedness				-0.139^{**} (0.055)	-0.019 (0.035)	0.105^{**} (0.050)
Political density				$\begin{array}{c} 0.520^{***} \\ (0.191) \end{array}$	0.306^{**} (0.140)	$0.197 \\ (0.223)$
Age	-0.008 (0.006)	-0.001 (0.003)	$0.003 \\ (0.003)$	-0.007 (0.006)	-0.001 (0.003)	$\begin{array}{c} 0.001 \\ (0.003) \end{array}$
Gender = man	$0.067 \\ (0.149)$	$0.001 \\ (0.070)$	-0.008 (0.083)	-0.005 (0.144)	-0.019 (0.069)	$\begin{array}{c} 0.001 \\ (0.079) \end{array}$
Low caste	-0.226 (0.171)	-0.151^{*} (0.091)	-0.182 (0.126)	-0.137 (0.155)	-0.150^{*} (0.088)	-0.203 (0.125)
Tribal caste	$\begin{array}{c} 0.663 \\ (0.459) \end{array}$	$0.101 \\ (0.209)$	$\begin{array}{c} 0.132\\ (0.312) \end{array}$	0.766^{*} (0.448)	$0.136 \\ (0.213)$	$0.168 \\ (0.293)$
Education	0.011 (0.014)	$0.005 \\ (0.009)$	0.023^{***} (0.008)	$0.022 \\ (0.016)$	$0.003 \\ (0.009)$	0.020^{**} (0.008)
Religious fractionalization	$\begin{array}{c} 0.306 \\ (0.387) \end{array}$	-0.079 (0.242)	$0.134 \\ (0.370)$	0.247 (0.396)	-0.266 (0.247)	$0.027 \\ (0.356)$
Caste fractionalization	$\begin{array}{c} 0.447 \\ (0.390) \end{array}$	-0.042 (0.273)	-0.267 (0.418)	$\begin{array}{c} 0.421 \\ (0.395) \end{array}$	$0.052 \\ (0.276)$	-0.218 (0.390)
Muslim	-0.107 (0.217)	-0.140 (0.123)	-0.334^{*} (0.196)	$0.089 \\ (0.218)$	-0.129 (0.120)	-0.354^{*} (0.196)
Asset index	0.079^{**} (0.036)	-0.054^{***} (0.018)	-0.061^{***} (0.019)	0.060^{*} (0.036)	-0.050^{***} (0.018)	-0.052^{**} (0.019)
N:	2522	5520	5594	2537	5551	5642

Table A.2. Effect of individual connectedness and neighborhood density on willingness to report theft of individual items. Errors clustered at slum-level.

Note:

	Dependent variable: Bribe paid to investigate theft of moto, rupees		
	(1)	(2)	
Count: Intercept	$ \begin{array}{c} (-) \\ 6.031^{***} \\ (0.246) \end{array} $	6.053^{***} (0.244)	
Count: Social connectedness	-0.165^{***} (0.040)		
Count: Social density	$0.065 \\ (0.154)$		
Count: Political connectedness		-0.012 (0.016)	
Count: Political density		$0.090 \\ (0.081)$	
Zero-Inflation: Intercept	-2.290^{***} (0.822)	-1.750^{**} (0.790)	
Zero-Inflation: Social connectedness	-0.388^{***} (0.089)		
Zero-Inflation: Social density	1.380^{**} (0.586)		
Zero-Inflation: Political connectedness		$0.028 \\ (0.075)$	
Zero-Inflation: Political density		0.083 (0.354)	
N:	958	932	
Note:		*p<0.1; **p<0.05; ***p<0.01	

Table A.3. Effect of individual connectedness and neighborhood density on amount paid in bribe. Zero-inflated negative binomial models. Errors clustered at slum-level. Control variables not shown.



Role of Informal Leaders in Slums

Key services that leaders reported providing for slum.

Figure A.3. Percent of leaders in structured interviews reporting having engaged in each type of activity.

	Dependent variable:		
	Social Connectedness	Political Connectednes	
	(1)	(2)	
Intercept	-0.911^{***}	-0.203^{*}	
-	(0.077)	(0.116)	
Age	-0.001	0.001	
	(0.001)	(0.001)	
Woman	-0.085^{***}	-0.206***	
	(0.024)	(0.033)	
Bangalore (2017)	1.313***	0.866***	
0 ()	(0.049)	(0.097)	
Jaipur	0.897***	-0.317^{***}	
1	(0.059)	(0.073)	
Patna	1.004***	-0.382***	
	(0.056)	(0.083)	
Muslim	-0.025	-0.070	
	(0.045)	(0.050)	
Christian	0.017	-0.005	
	(0.086)	(0.123)	
Wealth index	0.015**	0.036***	
	(0.008)	(0.010)	

Table A.4. Correlates of individual connectedness Models fit using	OLS, stan-
dard errors clustered at slum.	

Note:

*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:		
	Social Density	Political Density	
	(1)	(2)	
Intercept	-0.964^{***}	-0.769	
	(0.347)	(0.501)	
Religious frac.	-0.130	0.242	
0	(0.127)	(0.183)	
Caste frac.	-0.088	-0.136	
	(0.110)	(0.159)	
Settlement recognition	-0.065	0.283*	
C C	(0.106)	(0.153)	
Average wealth index	0.001	0.052**	
-	(0.017)	(0.024)	
Percent women	0.321	0.921***	
	(0.240)	(0.346)	
Average age	0.001	-0.003	
	(0.009)	(0.013)	
Bangalore (2017)	1.401***	0.840***	
	(0.071)	(0.102)	
Jaipur	0.869***	-0.394^{***}	
1	(0.070)	(0.101)	
Patna	0.959***	-0.386***	
	(0.076)	(0.109)	
Observations	159	159	
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A.5. Correlates of neighborhood density. Models fit using OLS. Oneobservation per slum.

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References

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