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Bribes, Bureaucracies and Blackouts: Towards Understanding How Corruption at the Firm Level Impacts Electricity Reliability

Jacquelyn Pless
Harrison Fell

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Colorado School of Mines
Division of Economics and Business
1500 Illinois Street
Golden, CO 80401

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Author(s):
Jacquelyn Pless
Division of Economics and Business
Colorado School of Mines
Golden, CO 80401-1887
japless@mymail.mines.edu

Harrison Fell
Division of Economics and Business
Colorado School of Mines
Golden, CO 80401-1887
hfell@mines.edu

ABSTRACT

This paper looks at whether bribes for electricity connections affect electricity reliability. Using detailed firm-level data, we estimate various specifications based upon repeated cross-sections and means-based pseudo-panels to show that bribes are closely related to poorer electricity reliability. We find that the propensity to bribe for an electricity connection is associated with an increase of 20 power outages per month and a 28% increase in annual sales lost due to power outages on average. The results parallel a tragedy of the commons story: electricity, which exhibits common-pool resource characteristics, suffers from overexploitation as self-interested individual firms rationally bribe for electricity, creating negative impacts in aggregate on the overall quality of the resource. Given the importance of electricity reliability for economic growth and development, the findings imply that improving oversight and enforcement measures at the consumer level targeting the reduction of bribery for electricity connections could contribute to growth and development.

JEL **classifications: O1, Q4**

Keywords: Corruption, Electricty, Reliability, Quality of Government, Institutions, Common-pool Resource

I Introduction

More than 1.2 billion people around the world are without electricity and 1 billion more have access to only unreliable power networks (UN, 2015). Unreliable and inadequate power can hinder or completely halt enterprise productivity, creating significant constraints on economic activity, growth, and human development. A handful of papers empirically illustrate these effects. For example, Andersen and Dalgaard (2013) demonstrate how weak power infrastructure leads to a substantial growth drag, Fisher-Vanden et al. (2015) show that electricity shortages significantly limit firm productivity, Rud (2012) studies electricity provision and industrial development and finds a strong relationship between electrification and manufacturing output, and Dollar et al. (2005) show that power losses have a statistically significant negative effect on productivity.[1] Poor electricity reliability also impedes the ability of households to conduct everyday activities, ranging from revenue generating and capacity building activities to social engagements. Humans rely critically on a secure and stable, high-quality supply of power, however improving reliability is characterized by vast complexity and is not strictly an issue related to investing in physical electrical infrastructure expansions and improvements. The problems are often symptoms of much deeper issues that transcend the boundaries of the electricity sector and are intimately tied to areas such as governance, corruption, fiscal policy, social equity, and political institutions.

As such, the underlying causes of poor electricity reliability are complex and critically relevant to policymakers, revenue-generating firms, and ultimately every member of society. In this paper, we focus on corruption at the consumer level and show how bribery for electricity connections is related to poorer electricity reliability as measured by power outages and their related commercial losses. Bribes made by consumers reflect rational self-interested behavior as firms seek to secure electricity connections in order to operate. However, in aggregate, we postulate that this bribing behavior overexploits the electrical grid, creating a weaker system that is more vulnerable to power outages. In light of this, these firms actually experience more power outages and incur greater commercial losses, which is contrary to the intuitive result of the bribe transaction resulting in more secure and reliable service provision.

Using detailed firm-level bribery and electricity reliability data, we form a dataset of repeated cross-sections including 72,617 manufacturing and services firms across 118 countries from 2006 to 2012. We also create a means-based pseudo-panel for an additional set of specifications. Instrumenting for the endogeneity of bribery with five firm-level instruments, our results across numerous robustness checks consistently show that bribes for electricity connections have a statistically significant correlation with more monthly power outages and their

[1] Furthermore, Eberhard et al. (2008) find that gross domestic product (GDP) losses due to power outages can be as high as 6 percent Kessides (1993) provides a comprehensive review of an older set of literature on the impacts of infrastructure on economic development, focusing mostly on the implications for economic growth but also highlighting the importance of infrastructure for improvements in other development indicators that capture quality of life.

related commercial losses. In the preferred specifications, we find that the propensity to bribe for an electricity connection is associated with an increase of 20 power outages per month and a 28% increase in annual sales lost due to power outages on average.[2] Interpreted differently, a one standard deviation increase in the propensity to bribe is associated with experiencing 7 more power outages per month and a 10% increase in annual sales lost due to power outages.

Our empirical setting is motivated by the observation that electricity networks exhibit common-pool resource (CPR) characteristics in which the resource (the shared electricity grid) faces the risk of being over-exploited due to a tension between individual rationality and social efficiency. It may be rational for individual firms to offer bribes to secure electricity connections for business operations, but in aggregate, such connections that create 'unmanaged demand' may overload the electrical grid. In this context, bribing serves as a proxy for over-use. Consider the case of a firm bribing a power supplier employee for an electricity connection. This employee may not disclose the activity to management, and thus the power that is supplied to the firm conditional on the bribe is not accounted for in the power supply model. Without knowledge of this bribe, management is left without a true estimate of the quantity of electricity it needs to provide to the grid and a supply-demand imbalance can occur, negatively impacting operational efficiency.[3] If there is a high incidence of this activity across firms sharing the same electrical wires, the system may become overburdened by the 'unmanaged demand'. This inefficiency can lead to system failure. Essentially, while one may reasonably expect that bribes for electricity ensure its provision, an abundance of this activity on a shared system may adversely impact the resource quality in aggregate. If we believe that bribing is a good proxy for over-use of electricity, then our results suggest that this overexploitation of electricity, due in part to consumer behavior, weakens the grid and makes it more vulnerable to power outages. This mirrors outcomes of the well-known CPR problem, constituting a type of social dilemma in which rationality at the individual level leads to an outcome that is not optimal from the perspective of the group. See Appendix A for more details on how electricity as a service exhibits CPR characteristics, with a particular focus on how electricity is rival and non-excludable.

To our knowledge, this paper is the first to study how corrupt behavior at the consumer level impacts the demand side of the electricity sector. A body of empirical research specifically focusing on corruption's implications for infrastructure sectors and growth has emerged over the past few

[2] According to the World Bank Enterprise Surveys, the data source for our outage data, a power outage occurs when there is equipment malfunction from the failure of adequate supply of power. Brownouts are also considered power outages. Respondents were asked to calculate the number of outages in a typical month, so if outages are seasonal, this does not include months in which outages are most frequent or when they are most infrequent.

[3] Expanding upon the traditional framework of thinking of natural resources, similar CPR stories are applicable to congestion and infrastructure such as traffic on highways. In the general CPR framework, individuals can consume a common resource to the individual's benefit but with an associated social cost: if aggregate consumption exceeds that which is supplied, the quality of the resource deteriorates or perhaps diminishes entirely. If overconsumption occurs in the form of bribes for electricity connections that are not accounted for in electricity providers' supply models, total demand can exceed that which is expected and supplied.

decades,[4] some of which focuses on electricity. While the question of how corruption, in its broad sense, impacts the power sector and its performance is not new, very few papers address the issue of reliability.[5] Most of the existing literature measures corruption at the country level (rather than consumer level) and focuses on the electricity sector supply side impacts (i.e., generation, transmission, and distribution) rather than demand side impacts (i.e., how end-users experience and consume electricity as a service through reliability). For example, a few studies have shown the adverse effects of corruption measured at the country level on electricity distribution efficiency and transmission and distribution (T&D) losses. Smith (2004) uses cross-sectional data to analyze how T&D losses vary according to country-level corruption perception indices. Similarly, Estache, Goicoechea, and Trujillo (2009) study the impact of country-level corruption and utility reforms on electricity supply efficiency. While the authors refer to T&D losses as a proxy for quality of service, T&D losses do not capture how the service reliability is actually experienced by end-users, such as through power outages or some other direct measure of reliability as felt by consumers. Lastly, Dal Bó and Rossi (2007) and Wren-Lewis (2013) consider political economy factors affecting the electricity sector at a more micro level, but they focus on how firms on the supply side (distribution) are impacted by corruption rather than those on the demand side.

Overall, our study makes three main contributions. Primarily, we offer the first empirical study of how consumer level corrupt behavior on the demand side of the electricity sector negatively impacts the reliability of power received, which is contrary to the intuition that bribing secures the intended rewards of reliable service. Offering insights into the nature of the electricity grid as a CPR, we motivate the importance of studying corrupt behavior at the consumer level and its impact in aggregate to offer insights into one angle for policy and governance interventions aiming to improve reliability. Second, we contribute to the small but growing literature on large socio-technical systems exhibiting CPR characteristics.[6] The problem of sharing common resources underlies many large-scale conflicts that are critical to a high functioning economy, from challenges related to global warming and the reduction of greenhouse gas emissions to the use of man-made resource systems like bridges and irrigation canals. First-best consumption of CPRs is often difficult, and thus consideration of these complex socio-technical systems from this perspective sheds light on institutional design and regulatory mechanisms for fostering second-best consumption. Lastly, given the importance of infrastructure and the reliability of its services for economic growth, this paper contributes a new insight for fostering development and growth more broadly.

[4] For instance, Fisman and Svensson (2007) show that bribery is negatively correlated with firm growth and Bah and Fang (2015) show that business environment—which includes a measure of corruption—is negatively associated with productivity and output in Sub-Saharan Africa.

[5] Infrastructure operations—such as electricity provision—are particularly vulnerable to corruption (Bergara, Henisz, and Spiller, 1998; Dal Bó, 2006; Estache and Trujillo, 2009) thus drawing increasing interest from researchers, decision-makers, and policymakers to explore mechanisms for reducing its impacts on infrastructure performance (Estache and Wren-Lewis, 2011).

[6] For instance, see Künneke and Finger (2009) and Kiesling (2009) for discussions of infrastructure systems as CPRs.

The remainder of this paper is organized as follows. In Section II, we describe our empirical model for the preferred specifications. We describe the data in Section III, results in Section IV, and robustness checks in Section V. We conclude with policy implications in Section VI.

II Empirical Model

We estimate the impact of the propensity to bribe for electricity connections on power outages and commercial losses due to power outages using repeated cross-sections, following the simple linear model for *i* firms:

$$y_i = \beta bribes_i + \gamma X_i' + v_t + u_n + sz_i + sc_i + \varepsilon_i \tag{1}$$

where y_i is electricity reliability for firm *i* (either the average number of power outages experienced by the firm monthly or the percentage of total sales lost due to power outages annually) and $bribes_i$ is propensity to bribe for an electricity connection. X_i is a matrix of firm- and country-level control variables described in Section III and v_t are year fixed effects to account for macroeconomic fluctuations, technology changes, and energy price shocks. We control for unobservables across countries with country fixed effects, u_n, capturing inherent differences in power system characteristics.[7] Firm size dummies, sz_i, control for differences in power outages experienced across firms of different sizes, sector fixed effects, sc_i, capture the importance of electricity as an input to operations, and ε_i is the disturbance term.

There are three identification concerns that could lead OLS estimation of Equation 1 to produce biased estimates of β. First, bribery could be endogenous due to simultaneity bias. One can imagine that firms have an incentive to bribe for electricity connections or a more secure service if the electricity infrastructure is in poor condition already. In other words, perhaps it is not the case that bribery for electricity connections leads to more power outages but rather that the existence of a weak electricity infrastructure that suffers from a high incidence of power outages provides firms with an incentive to bribe for a more secure service. If this is the case, then our specification suffers from simultaneity bias. We use an instrumental variables (IV) strategy to account for the endogeneity of bribery behavior with the instruments described in Section III.

Second, we are unable to separately identify the effect of bribery and country fixed effects without intra-country variation in bribery. In our sample, we include only firms located in countries with intra-country variation in the propensity to bribe. Ideally, to examine this CPR setting, we would have grid-level data to identify the aggregated effect of firm bribes on grid reliability. Given our firm-level data that do not include location identifiers, we rely on the assumption that

[7] We also estimating specifications that interacted year and country fixed effects to capture countrywide trends and the results were the same.

electricity grids and their territories are defined sub-nationally and that a firm's propensity to bribe is representative of bribe propensity of other firms extracting power from the same grid.[8]

Third, electricity reliability could be correlated with shocks at the firm level over the time period, and our repeated cross-sections do not allow us to include firm-level fixed effects as we would in a traditional panel setting. As such, we create a means-based pseudo panel in which cohorts of firms with similar characteristics are tracked over time to strengthen our identification strategy. Section III describes the characteristics on which we group observations. The observations for each cohort consist of averages of the variable values so that what results is a pseudo panel with repeated observations for C cohorts over T periods. The model specification for pseudo-panel regressions is written generally as

$$\bar{y}_{ct} = \beta \overline{bribes}_{ct} + \gamma \bar{x}'_{ct} + \bar{u}_c + \bar{v}_t + \bar{\varepsilon}_{ct}\ ,\ \ c = 1, \ldots, C;\ \ t = 1, \ldots, T, \quad (2)$$

where $\bar{y}_{ct}$ is the average value of all observed y_{ct}'s within cohort c in period t, and likewise, the other variables are also averages of observed values within each cohort c in period t. Here, $\bar{u}_c$ are cohort-level fixed effects (the average of firm fixed effects in cohort c). Identification rests upon within cohort variation for a given year and variation over time for a given cohort. Year fixed effects allow for time effects to be accounted for in a flexible way, measuring the impact of sector trends, and time-invariant unobservables at the cohort level are controlled for with cohort fixed effects. This method of averaging within cohorts also helps to remove potential measurement error at the firm level (Antman and McKenzie, 2007). One last challenge to bear in mind is that the number of firms in each cohort and time period is not the same, which could induce heteroskedasticity. We follow Dargay (2007) and Huang (2007) to correct for this by weighing all cohort variables by the square root of the number of firms in each cohort. Because bribery is still endogenous, we implement the same instrumental variable approach as in the repeated cross-section regressions.

III Data

Our dataset includes both firm-level and country-level variables that come from three different public databases. We collect firm-level data from the World Bank Enterprise Surveys, including information on topics that span electricity infrastructure, corruption, and performance measures.[9] We match firms to country-level data from the World Bank's Development Indicators Database[10] for various control variables and the World Bank's Governance Indicators Database[11] for country-level corruption and governance controls. Our full dataset covers 72,617 firms across 118 countries from 2006 to 2012. Once we omit firms that are in countries without intra-country variation in

[8] If firms extracting power from the same grid provide different answers regarding the need to bribe, then both the magnitude and significance of our parameter estimates will be lower, making our estimates upper bounds.
[9] Available at enterprisesurveys.org.
[10] Available at http://data.worldbank.org/data-catalog/world-development-indicators.
[11] Available at http://info.worldbank.org/governance/wgi/index.aspx#home.

bribery propensity, our sample includes 69,283 observations across 104 countries. Table 1 provides the summary statistics for this preferred dataset, which is what we use throughout our main analysis. There is substantial variation in each of the variables across firms as well as across countries. Table B1 in Appendix B provides the same summary for the full dataset.

Table 1: Summary Statistics of Key Variables

	Number of Observations	Mean	Standard Deviation	Min	Max
Reliability Measures					
Outages (monthly avg.)	38,753	12.52	26.6	0	600
Losses (% of total sales)	23,199	7.667	11.73	0	100
Bribery in Electricity Sector					
Propensity to Bribe	11,858	0.14	0.347	0	1
Firm-Level Controls					
Working Capital (% internal)	57,919	69.43	34.89	0	100
Public (indicator)	68,493	0.0601	0.238	0	1
Percent Private	67,800	89.13	29.09	0	100
Generator Ownership (indicator)	49,307	0.288	0.453	0	1
Sales (annual) (LCUs)	61,483	7.76E+10	1.15E+13	0	2.70E+15
Country-Level Controls					
GDP per Capita	67,166	10,024	6,929	568.6	29,321
Population Density	69,283	104	175.8	1.72	1,125
Inflation (%)	64,684	6.416	5.78	-2.41	34.7
Government Indicator Average	69,283	-0.0369	0.536	-1.584	1.77

Source: World Bank Databases

Our primary variable of interest, bribery, is measured by whether the firm reported in the Enterprise Surveys that informal gifts or payments are generally expected or required in order to obtain an electrical connection (1=yes or 0=no).[12] Although this measure is not an explicit indication of executed bribes, we assume that a higher propensity to bribe for electricity connections (or the perception of its necessity for obtaining an electricity connection) is reflective of higher incidence of bribery for electricity connections in the region that the firm is operating.[13] In

[12] Some may question whether reliable firm-level data on corruption can be collected—it is often the view that it is near impossible to collect reliable quantitative information on corruption given the secretive nature of corrupt activities (Reinekka and Svensson, 2002). However, Kaufmann (1997) argues that with appropriate survey methods and interview techniques, firm managers are willing to discuss it with relative candor, and firm managers can be given the right incentives to cooperate and truthfully report their experiences. While survey data are never perfect, the Enterprise Surveys are the most robust resource for the firm-level variables we wish to study.

[13] The way in which we observe bribery does not allow us to identify the effectiveness of bribes in obtaining electrical connections or securing reliable power since the data do not explicitly track whether a bribe was successful in guaranteeing service. In fact, the bribery measure does not even capture whether bribes were executed or bribes for turning power on and off—it just proxies for the potential initial connection itself and whether firms are more likely to need to bribe for electricity. Our objective is not to ask whether bribes are effective mechanisms for obtaining secure power but rather to understand whether more bribery incidence overburdens the grid enough to contribute to power outages.

this context, a higher incidence or likelihood of bribing at the firm level is likely associated with a higher incidence of bribery on that firm's electrical grid in aggregate. As a proxy for grid failure, we consider two firm-level variables that reflect the quality of service received: average number of monthly power outages and percentage of total annual sales lost specifically due to power outages.[14] We assume that more frequent power outages at the firm level are related to more frequent outages on the broader network from which that firm extracts power.[15] We discuss how we address this potential sensitivity with robustness checks in Section V.

One also may be concerned that a propensity to bribe is correlated with poor country management or infrastructure, which impacts the electricity sector and reliability. The World Bank Development Indicators Database and the World Bank Governance Indicators Database provide country-level data on important economic and governance variables that underlie the overall infrastructure conditions within a region, providing us with controls for inherent weaknesses and vulnerabilities in the electricity system that could be contributing to power outages. Specifically, we include three country-level macroeconomic variables that are related to the potential quality of infrastructure: GDP per capita (PPP constant 2005 international dollars), population density (people per square km of land area), and the inflation rate (based on the consumer price index). We assume that wealthier countries generally have more resources available for investing in infrastructure, which could enhance the baseline quality and stability of the electricity system. Population density is included since it is sometimes suggested that T&D losses, a proxy for the stability of a power system, are related to population density.[16] Inflation rate is included to proxy for general macroeconomic instability and its relation to infrastructure conditions.

Additionally, the World Bank Governance Indicators Database provides data that capture six broad aspects of governance and corruption at the country-level.[17] Each index ranges from -2.5 (weak governance) to 2.5 (strong governance). Including these in our analysis helps us to control for the impact of broader institutional weaknesses and vulnerabilities that contribute to the quality and management of infrastructure services. The energy sector is a prime target for, and source of, corruption, and it is often riddled with other governance issues. For instance, a few attributes that contribute to this vulnerability include the potential for generating considerable economic rents, the need for large capital investments, and the central role of government agencies. There is often a lack of transparency of decision-making as well as a dearth of effective legal systems for reducing the risk of decision-makers abusing their power. Because the governance indicators are highly

[14] Both of these variables are self-reported estimates provided by firm management in the Enterprise Surveys.

[15] Although some of these outages could be planned, our data do not differentiate between planned outages and unplanned outages, and thus we take the monthly estimates as being proxies for total outages. If there is bias due to unplanned outages, it is likely relatively consistent across entities once we control for the firm's country location.

[16] See MIT (2011) for discussion.

[17] The measures include voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption. These measures combine the views of citizens, enterprises, and expert survey respondents based on 32 individual data sources from non-governmental organization, international organizations, private sector firms, and think tanks.

correlated with each other and capture similar uncertainties that impact investment and operating conditions, we average the six indicators to create a single 'governance quality' control variable.[18]

We include one firm-level control variable that is intended to capture a broader countrywide characteristic that is related to infrastructure quality: access to finance. Provision of end-user finance is often needed to overcome the barriers related to the high initial capital costs associated with gaining access to energy services. More working capital from internal sources rather than banks or microfinance arrangements may imply access to finance barriers in the economy, which are commonly cited as a major obstacle to investing in and improving electricity infrastructure and thus the quality of energy services (UNEP 2012). We proxy for this barrier with the percentage of the firm's total the working capital that the firm finances with internal sources.

We also may be concerned with firms receiving preferential treatment in ways that could impact the quality of electricity provided to the firm. For instance, if a firm (or firms within a certain industry) contributes significantly to the economy, it may have more bargaining power to ensure that it receives high quality electricity. We include total annual sales (logged) to control for this, assuming that high sale figures reflect a large contribution to the economy and the potentially for receiving preferential treatment. Two variables related to firm ownership are also included with the intention of capturing factors corresponding to heightened perceptions of corruption (Galang et al., 2013) and dealings with public officials in acquiring certain services (Rienikka and Svensson, 2002): public ownership (as an indicator variable) and the percent of the firm that is privately owned. Some evidence has shown that state-owned firms have a lowered sensitivity to corruption, and the fusion of firm ownership with the state can make firms less sensitive to the negative impacts of corruption, potentially influencing the relationship between the firm and service provider in a way that impacts the quality of service provided. Furthermore, private firms often bear the brunt of corruption whereas state-owned firms that benefit from the state could be more likely to turn a blind eye to the activity (Galang et al., 2013). Other work has shown that firms dealing with public officials whose actions directly affect the firm's business operations usually have to pay bribes, such as when acquiring public infrastructure services (Reinikka and Svensson, 2002). Each of these factors could contribute to a firm receiving preferential treatment in electricity service provision.

Lastly, we include generator ownership as a control variable since it may indicate that the firm will not need to bribe for an electricity connection if power is lost given its backup source of electricity. If a firm owns a generator, then there is little to no need for electricity connection bribes since onsite generation is possible in the face of poor reliability. Furthermore, firms owning generators in the first place may indicate an anticipation of poor service, which may be reflective of the baseline electricity system quality.

[18] We also ran regressions with each indicator included separately and our results remained stable.

We propose a set of five firm-level instruments for bribery: female ownership, foreign ownership, obtainment of an internationally recognized quality certification, age of the firm, and the practices of competitors in the informal sector being a major obstacle to operations. Our choice of instruments was motivated by a review of the literature that empirically explores the determinants of bribery. Female ownership and foreign ownership both have been shown to be associated with a lower propensity to bribe (Swamy et al., 2001; Dollar et al., 2001; Clarke, 2014). When women are better represented in government and the workforce, less corruption pervades. Foreign-owned firms may have a stronger incentive than domestic firms not to pay bribes because foreign investors in developed economies might be concerned about the laws in their home countries (Lee et al., 2007; Clarke, 2014). We measure female ownership as a dummy variable (equal to one when firms have any female participation in ownership). We measure foreign ownership as the percentage of the firm that is foreign-owned because firms' bargaining power increases as its percentage of foreign ownership increases, and a firm's bargaining power impacts whether bribes are demanded of them. We expect higher percentages of foreign ownership to be associated with a lower vulnerability to corruption and less propensity to bribe (Lee et al., 2007).

Similarly, we suspect that firms that have obtained international quality certificates may be less likely to bribe. We measure this as an indicator variable based on the Enterprise Survey question about whether the firm has received a certification related to quality management from the International Organization for Standardization (ISO). We assume that the management of these firms maintains transparency and enforcement guidelines that help to reduce their tendency to fulfill bribe demands or to offer bribes. Furthermore, obtaining international quality certifications could improve the motivation, awareness, and morale of employees (World Bank, 2014), potentially reducing the firm's propensity to bribe.

Age of the firm is used as an instrument because of the notion found in the literature that older firms might have different experiences than younger firms when interacting with government officials. New firms may be less visible and incur fewer bribe demands. On the other hand, new firms may require more permit and license applications, possibly demand more bribes because of more frequent interactions with government officials (Clarke, 2014). Nonetheless, the age of the firm has been cited as being related to bribery propensity, as demonstrated in Lee et al. (2007). We follow Lee et al. (2007) and measure age of the firm by the number of years since foundation.

Lastly, we instrument with a measure of how severe of an obstacle the informal sector is to firm operations. In many developing countries, the informal sector is a major engine for employment and growth (Schneider, 2002). There are numerous motivations for firms to operate underground (Johnson et al., 1997; Johnson et al., 1998; Johnson et al., 2000; Johnson et al., 2001; May et al., 2002), and operating unofficially is sometimes considered to be a mechanism for avoiding the predatory behavior of government officials that seek bribes from those with officially registered activities (Lavallée and Roubaud, 2009). At the same time, entrepreneurs may bribe public officials in an attempt to secure their informal activities, and indeed, informal sector firms may be exposed to demands for bribes even more so than formal firms (Lavallée and Roubaud, 2009). If firms believe they are competing with other firms that are bribing, such as those in the informal sector, there may be a greater incentive to also supply bribes to secure services. In other words, if firm management believes the informal sector is an obstacle to operations and that firms in the informal sector are bribing, it may believe it also needs to bribe in order to maintain a competitive advantage. We use the response to one of the questions on the Enterprise Surveys to proxy for this that asked firms to rank the severity of the obstacle on a scale from 1 (not severe) to 4 (very severe).

It is possible that these instruments could be correlated with country-level institutions and unobserved conditions that we cannot control for in our analysis. For instance, there may be some unobserved characteristic of a country's cultural environment that impacts the likelihood of female participation in ownership, or perhaps fewer firms in certain countries obtain quality certifications because the business climate makes it nearly impossible to meet the standards. Furthermore, perhaps firms view the informal sector as a severe obstacle because it is indeed a more significant component of the economy in countries characterized by a less stable business climate. It is not possible to test whether these instruments indeed are correlated with unobserved determinants of power outages, however we can examine the correlations between the instruments and other covariates, which are intended to capture the underlying macroeconomic fabric within which the firms are operating and could be correlated with similar unobservables, to provide evidence that our choice of instruments have strong theoretical grounding.

Table B2 in Appendix B presents the correlation matrix. We can see that the instruments exhibit extremely low correlations with nearly all of our other covariates, mostly with correlations under 0.10. This gives us more confidence that our instruments are not correlated with unobserved determinants of power outages. There are a few exceptions, however. For instance, foreign ownership is highly correlated with private ownership ($\rho = -0.90$). To account for this, we run regressions with various combinations of the instrument set as a robustness check.

Finally, designing and setting up pseudo panels is not trivial. Cohorts must be groups of firms that share common characteristics, where each firm is a member of only one cohort, and cohorts must have fixed membership based on characteristics observed for all observations within the sample. One natural characteristic to base cohort groupings upon is region of operation. Unfortunately, because we do not have enough countries that are repeated consecutively through the sample period, grouping on country is not effective. As such, we group based on geographic region following the World Bank classifications. Grouping only on region, however, is extremely limiting. Therefore, we group on two other firm attributes that likely affect a firm's bribery behavior—firm size and sector—and one other country-level variable that captures the broader corruption climate as a proxy for the propensity to engage in corrupt activities, the 'control of corruption' World Bank Governance Indicator.

Our selection of firm size was motivated by empirical research showing that it may be related to bribing behavior (Abed and Gupta, 2002; Anderson and Gray, 2006; Lee et al., 2007).[19] Firm size is defined by the number of employees, where 5-19 employees indicates the firm is small, 20-99 is medium, and 100+ is large. Because size is still a relatively crude instrument on which to group, we also group on sector as a characteristic affecting the incentive to bribe. The choice of sector is motivated by it being a proxy for electricity demand or the firm's reliance on electricity for operations and revenue generation. For example, both Apple and Ford are large companies, but their energy consumption profiles are unlikely to be similar. Therefore, their propensity to bribe for power is probably different since their business models rely upon it differently. Essentially, grouping by sector aims to capture the firm's reliance upon electricity, supported by studies that have shown that firms in different industries exhibit different bribing behavior.[20]

Grouping firms based on 'control of corruption', which characterizes the conditions of the country in which each firm operates, helps us to overcome the challenge of not being able to group on country itself. Perhaps more importantly, it captures the macro-level conditions that we expect would impact a firm's propensity to bribe. The World Bank defines 'control of corruption' as 'the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests'. The metric also measures the strength and effectiveness of a country's policy and institutional framework to prevent corruption. One can imagine that a weaker control of corruption as defined in this way may enable more bribery. Furthermore, bribery is not just a problem related to corrupt behavior by firms offering bribes. Just as in any transaction, bribery transactions have both a supply side and a demand side. Officials with the power to offer government contracts, issue a license, or allocate some scarce resource can demand bribes, as well (Dixit, 2013). This directly relates to 'control of corruption', which captures bribery demand.

The control of corruption measure is an index combining up to 22 different assessments and surveys, each of which receives a different weight based upon estimated precision and country coverage. The indicator ranges from -2.5 (weak) to 2.5 (strong). We group firms based on which quartile they fall within based on the range of this measure in our sample. Again, we face the concern that this measure could change for firms over time, however we are not too concerned since the pace of change can be quite slow depending and depend on building the foundations for reform (Johnston, 2014).

[19] These studies show that smaller firms pay bribes more frequently and pay more bribes as a share of revenues relative to larger firms.

[20] Some studies have shown that there are industry level differences in bribery (Clarke, 2014). For instance, Herrera and Rodriguez (2003) show that manufacturing firms are less prone to bribe than service sector firms. Lee et al. (2010) show that firm size is negatively associated with the likelihood of bribery.

IV Results

Table 2 presents our main results.[21] The estimates consistently suggest that a higher propensity to bribe for an electricity connection is associated with more power outages and their related losses, or in other words, a less reliable electricity system. The coefficient estimates for bribery can be interpreted as the change in monthly power outages and the change in financial losses as a percentage of total sales, on average, associated with the propensity to bribe for electricity connections. When using an IV approach and including all controls, the propensity to bribe is associated with an increase of 20 power outages per month on average, which is statistically significant at the 5% level. Interpreted another way, an increase in the propensity to bribe by one standard deviation is associated with about 7 more power outages per month. Furthermore, the propensity to bribe is associated with a 28% increase in financial losses due to power outages, or a one standard deviation increase in the propensity to bribe is associated with a 9.8% increase in losses (significant at the 5% level). For robustness purposes, Tables B6 and B8 in Appendix B provide sets of regression results where we add one control variable at a time to the IV specifications for outages and losses, respectively, in order to be more confident that the results are not driven by some unobservables related to our control variables. We see that the results are statistically significant in all cases and the magnitudes of the coefficient estimates are relatively stable.

Table 2: IV Regressions for Monthly Power Outages and Financial Losses Due to Outages

	Outages	**Outages**	**Losses**	**Losses**
Propensity to Bribe for an Electricity Connection	**18.13 ****	**20.51 ****	**14.03 ***	**28.29 ****
	(8.46)	**(9.29)**	**(8.33)**	**(12.41)**
Firm-level controls	No	Yes	No	Yes
Country-level controls	No	Yes	No	Yes
Country Dummies	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes
Firm Size Dummies	Yes	Yes	Yes	Yes
Time (year) Dummies	Yes	Yes	Yes	Yes
Observations	3567	2106	1638	968
F-statistic	4.89	6.05	4.43	4.02
Under identification test (p-value)	0.0097	0.004	0.007	0.036
Over identification test (p-value)	0.546	0.878	0.606	0.745

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[21] We do not include naïve (non-instrumented) regression results since the simultaneity bias renders such results invalid. However, we have confirmed that the direction of the bias is correct. When we do not instrument, the effect of bribes on outages is zero, implying a negative bias. We regressed bribe propensity on outages along with all controls and IVs as regressors and we found a negative coefficient estimate for outages. This can be explained by the lack of incentive to bribe for an electricity connection once outages are so frequent that purchasing a backup generator is a more reasonable substitute. The same exercise for financial losses confirms the direction of bias for those regressions as well.

The findings from the pseudo-panel regressions also consistently support the conclusion that bribery adversely affects electricity reliability however the magnitudes of the parameter estimates are much higher. When including both cohort and time fixed effects in IV regressions, the propensity to bribe is associated with higher levels of both outcome variables. Table 3 summarizes these results, showing how we find positive and statistically significant coefficient estimates. Specifications 1 and 2 include all controls, and we drop the governance indicator average control variable in specifications 3 and 4 since this variable encapsulates one of the variables on which we formed the cohorts ('control of corruption'). We present the first stage results for specifications 1 and 2 in Tables B10 and B11 of Appendix B, respectively. Examination of the first-stage regression results reveals that the instruments are stronger for the pooled OLS regressions. As such, we prefer the pooled OLS IV regression results presented in Table 2 given their slightly stronger first-stage results and the loss of statistical power in the pseudo-panel regressions.

Table 3: Pseudo-Panel Regression Results, Instrumental Variables Approach
Grouping on region, sector, firm size, and 'control of corruption' in host country

	Outages (1)	Losses (2)	Outages (3)	Losses (4)
Propensity to Bribe for an Electricity Connection	**46.65 ***	**64.57 *****	**52.04 ***	**48.71 ****
	(26.96)	**(20.24)**	**(26.87)**	**(21.80)**
Firm-level controls	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	w/o Gov. Avg	w/o Gov. Avg
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Time (year) Fixed Effects	Yes	Yes	Yes	Yes
Observations	302	239	302	239

Robust standard errors in parentheses; errors are clustered on country
*** p<0.01, ** p<0.05, * p<0.1

V Robustness Checks

To be sure our results hold when including all firms, we run IV regressions on the full dataset and show that the propensity to bribe for electricity connections is still statistically significant for both outcome measures and stable in magnitude with our previous findings (see Table 4). We also conduct a similar exercise as with the preferred specifications to demonstrate that the magnitude and significance of coefficient estimates are stable despite which control variables are included, and these results are provided in Tables B12 and B13 in Appendix B for outages and commercial losses, respectively. The estimates fall within a similar range as they did in the preferred specifications (15 to 22 for power outages and 15% to 30% for losses).

Table 4: IV Pooled OLS Regression Results for Full Dataset

	Outages	Losses
Propensity to Bribe for an Electricity Connection	**22.01 ****	**30.40 ****
	(9.75)	(13.15)
Observations	1032	2183
F-statistic	6.003	3.69
Under identification test (p-value)	0.004	0.043
Over identification test (p-value)	0.885	0.746

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Both specifications include firm-level and country-level controls, and country, sector, firm size, and year dummies.

The second biggest concern is that even though there exists within-country variation in bribery, the data do not allow us to attribute individual firms to specific grids in order to capture some aggregated grid-level impact. This creates uncertainty as to whether spatial heterogeneity actually exists. Therefore, we run regressions on data from firms only located in geographically large countries to see if the results hold when we are more confident that respondents are indeed spatially dispersed. We first define 'geographically large' as countries that are geographically larger than the Q3 size found in our dataset, which is 1,280,000 square kilometers. Our results for power outages and financial losses are presented in specifications 1 and 2, respectively, of Table 5. The findings hold for power outages, however significance is lost in the financial losses regressions. We consider two additional definitions of 'geographically large': countries that are 2 million square kilometers or larger and those that are 4 million square kilometers or larger, which were two cutoffs that appeared to be natural breaking points when plotting the data. We present these results in Table 5 as well. Columns 3 and 4 present the results for countries larger than 2 million square kilometers. Columns 5 and 6 present the results for countries larger than 4 million square kilometers. For countries greater than 2 million square kilometers, the results maintain significance for power outages but it is lost again for financial losses. For countries greater than 4 million square kilometers, significance is maintained for both outcome measures.

A positive coefficient estimate for each regression and significance for each regression is maintained on outages. While the F-statistics indicate that these regressions suffer from weak instrumentation, specification 1 has greatest power while also exhibiting a relatively high F-statistic, and thus it is our preferred specification of this set. Demonstrating that bribery propensity maintains a positive coefficient that is significant at the 5% level while instrumenting and with all controls on this set of geographically large countries provides us with more confidence that our data exhibit spatial heterogeneity in bribery propensity.

Table 5: IV Pooled OLS Regression Results for Geographically Large Countries

	Outages (1)	Losses (2)	Outages (3)	Losses (4)	Outages (5)	Losses (6)
Propensity to Bribe	**5.40 ****	**0.411**	**3.22 *****	**5.45**	**2.61 ****	**6.82 ***
	(2.54)	**(8.59)**	**(0.99)**	**(3.60)**	**(1.09)**	**(3.77)**
Observations	646	224	322	105	322	105
F-statistic	12.34	0.551	2.21	0.565	2.48	0.861

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Note: Each specification is instrumented. All specifications include firm-level and country-level controls, and country, sector, firm size, and year dummies. Specifications differ according to the cut-off in country geographic size for defining 'geographically large'. Columns 1 & 2 consider countries that are geographically larger than the Q3 size in our dataset as 'geographically large'; Columns 3 & 4 define geographically large as larger than 2 million square kilometers; Columns 5 & 6 define geographically large as larger than 4 million square kilometers.

A third concern that arises is that not all five of the instruments are significant determinants of bribery for electricity connections, as demonstrated by the first-stage regression results.[22] While the informal sector obstacle variable and age of firm are significant predictors at the 1% level in the first-stage regressions for both outcome variables, the other three IVs are not. Therefore, we want to be sure that our results are not sensitive to which instruments we include. We run five additional instrumental variable regressions for each outcome measure, adding one instrument at a time, and find that the results are relatively consistent across specifications. When regressing on power outages, in all specifications except for one, we maintain significance and find that bribery is associated with 19 to 21 more power outages per month (see Table 6). Similarly, when regressing on commercial losses, in all specifications except for one, we maintain significance and find that bribery is associated with an increase in losses 20% to 40% of annual sales (see Table 7). For the two specifications where significance is lost, the coefficient estimates remain positive. These findings are consistent with those in our preferred specifications. Our results pass the under- and over-identification tests, and thus we favor inclusion of the entire set of IVs in the preferred specifications given our review of the literature and the theoretical justification for their inclusion.

[22] Also, our F-statistics are low, which may be problematic.

Table 6: IV Robustness Checks for Pooled OLS Regressions - Outages

Propensity to Bribe	**13.77**	**19.45 ***	**21.45 ****	**21.26 ****	**20.51 ****
	(16.11)	**(10.83)**	**(10.23)**	**(9.74)**	**(9.29)**
Included Instruments					
Informal Sector Obstacle	X	X	X	X	X
Age of Firm		X	X	X	X
Quality Certification			X	X	X
Female Ownership				X	X
Percent Foreign					X
Observations	4215	2413	2322	2106	2106
F-statistic	6.82	8.82	7.58	5.26	6.05

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: All specifications include firm-level and country-level controls, and country, sector, firm size, and year dummies.

Table 7: IV Robustness Checks for Pooled OLS Regressions - Commercial Losses

Propensity to Bribe	**40.32 ***	**13.52**	**20.65 ***	**24.45 ***	**28.29 ****
	(20.87)	**(12.95)**	**(12.18)**	**(12.88)**	**(12.41)**
Included Instruments					
Informal Sector Obstacle	X	X	X	X	X
Age of Firm		X	X	X	X
Quality Certification			X	X	X
Female Ownership				X	X
Percent Foreign					X
Observations	2455	1155	1117	968	968
F-statistic	6.05	5.78	5.29	3.61	4.02

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: All specifications include firm-level and country-level controls, and country, sector, firm size, and year dummies.

Lastly, it is possible that the way in which we chose to group firms for forming the pseudo-panel introduced bias since the selection of attributes on which to group were largely motivated by existing studies in the literature. One attribute that might be particularly troubling is our choice of grouping firms based on the region in which they are located. Each region includes numerous countries of varying macroeconomic conditions, institutional challenges, cultures, and more. We consider omitting this variable as one that we group upon and group firms based on only firm size, sector, and 'control of corruption'. While firm size and sector are both cited as potential determinants of firm-level bribing behavior, 'control of corruption' still captures the broader country-level stability that may influence a firm's behavior. The results from these regressions, when instrumenting with the full set of instruments and including all controls, are provided in B14 of Appendix B. Once again, the positive coefficient estimate is maintained for power outages at the 5% level. While significance is lost when regressing on commercial losses, the sign remains positive.

Overall, the robustness checks demonstrate that the positive coefficient findings are maintained with significance in all cases when regressing on monthly power outages, but the significance of results when regressing on commercial losses is more sensitive to the selection of data and instruments. Nonetheless, the positive coefficient estimate is maintained across all robustness checks. Furthermore, the power outages outcome is the measure that more directly captures the phenomenon that we aim to measure in this analysis. The goal is to identify whether more illegal consumption of electricity contributes to a less reliable electricity system as measured by its failure. Monthly power outages are a direct reflection of power system failures, while commercial losses due to power outages are normalized to total firm sales and could be influenced by the firm's dependence on electricity for operations and profitability as opposed to strictly capturing the occurrence of power outages. It is possible that the firm-level controls and various sets of fixed effects did not fully control for this influence.

The positive coefficient estimates of consistent magnitude maintained across all robustness check specifications when regressing on power outages provides us with more confidence in our findings. That is, our results suggest that bribes for electricity connections are closely related to poor electricity reliability.

VI Conclusion

Previous work has demonstrated the importance of electricity reliability for economic growth and development, however the underlying causes of poor electricity reliability in developing countries have gone relatively unstudied. We aimed to narrow this gap in the literature by focusing on the role of corruption and its impact on reliability, offering the first empirical study to our knowledge of how consumer-level corrupt behavior on the demand side of the electricity sector negatively impacts the service provided. In our analysis, the propensity to bribe for an electricity connection is associated with an increase of 20 power outages per month and a 28% increase in annual sales lost due to power outages on average. Our results are robust across a range of specifications based upon repeated cross-sections and a means-based pseudo-panel, showing that bribes are closely related to poorer reliability. This implies that one effective governance intervention for improving reliability may be to focus on reducing bribes for electricity connections, perhaps through enhanced transparency, oversight, and enforcement.

Furthermore, we argue that our findings can be explained in the context of the well-known CPR problem, where rationality at the individual level leads to an outcome that is not optimal from the perspective of the group. Studying corruption at the firm level allowed us to observe what appears to be rational self-interested behavior—bribes for electricity connections—and correlate it with an outcome that proxies for reduced quality of service: power outages. Power outages occur more frequently when a system is weak, and if we believe that bribery for electricity connections is a reasonable proxy for over-consumption, then these bribes facilitate a weaker state of the electrical system that is more vulnerable to failure. This phenomenon parallels a tragedy of the commons story: when users fail to internalize the congestion costs that they impose on others, inefficient consumption occurs and resource quality diminishes.

Ensuring adequate electricity reliability is complex, particularly in a developing country context. The challenges extend far beyond the capacity to invest in the physical infrastructure. It was the aim of this paper to highlight the relevance of just one of these underlying issues—corruption—and shed light on the potential of policies and governance interventions that focus on reducing corruption at the consumer level in the quest for improving electricity reliability.

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Appendix A: Electricity as a Common Pool Resource (CPR)

A CPR is a resource system (natural or man-made) that is sufficiently large to make it costly (but not impossible) to exclude consumers from obtaining benefits from its use, exhibiting both rival and non-excludable characteristics (Ostrom, 1990). Such goods are rival (or *subtractable*) in the sense that multiple individuals can use the system while each individual's consumption subtracts from the total quantity available to others. CPRs are *non-excludable* in the sense that it is difficult to keep those who have not paid for the good from consuming it. While CPR classifications are traditionally used to describe natural resource systems such as river basins, lakes, and forests, large socio-technical systems also fit within this framework, receiving limited attention in the literature to date despite their increasingly frequent CPR-related problems such as congestion and overuse, access regulation that prevents excessive appropriation, and poor investment incentives (Künneke and Finger, 2009).

Electric power itself—the actual electrons consumed—is a pure private good. As individuals extract electrons from the grid, they subtract from the total quantity available to others.[23] However, viewing electricity as strictly 'electric power' ignores the physical realities of electricity as it is actually transmitted, delivered, and consumed by end-users. That is, when individuals, households, and firms consume electricity, they are actually consuming a bundle of valued goods—electric power itself (the electrons), as well as reliability, voltage, and frequency (Toomey et al., 2005). Because each of these components relies upon the others, this bundle cannot be disaggregated. We cannot consume electric power without its associated voltage, and reliable power cannot be delivered without adequate voltage and frequency conditions in its associated wired network. For example, when there exist deviations in network frequency or voltage, generators can trip and the entire system can fail, leaving those connected to the system without electric power (Joskow and Tirole, 2007).

While it is the electric power component of the bundle that makes electricity subtractable, it is the voltage, frequency, and reliability components that make it non-excludable. Regardless of what is paid by individual customers, and even despite differences in the actual power demanded and received, consumers on the same network share the same voltage, frequency, and probability of a power outage.

To elaborate, there are at least two explanations for electricity being non-excludable that are related to the interdependence of these bundle components. First, systems are often spread across large geographical areas with difficult to monitor access points. While it is possible to track power consumption and identify irregularities with some precision given existing metering technology, not every "leak" in the distribution grid can be tracked because of the existence of non-technical losses (NTLs). There are two different types of electricity losses[24]: technical losses, which are caused by losses in transmission or deficiencies in operations and physical infrastructure,[25] and NTLs, which reflect inefficiencies resulting from actions outside of the physical power system. Common causes of NTLs

[23] The only context in which multiple people can consume the same electrons is in a shared lighting space.
[24] Electricity losses refer to electricity injected into a transmission and distribution grid that is not paid for by final end-users.
[25] These are inherent to the current transportation and associated with the infrastructure characteristics of the power system itself, consisting mainly of power dissipation in electrical system components such as transmission lines and transformers (Suriyamongkol, 2009).

include electricity theft, non-payment, and poor recordkeeping and oversight (World Bank, 2009). Any type of illegal connection to the power grid can be classified as electricity theft, and NTLs are most significant in countries characterized by relatively high economic, social, and political risk (Smith, 2004).[26]

Although technical losses can be tracked and optimized, as this is simply an engineering issue that involves power system planning, NTLs are much more difficult to measure since actions external to the system are unaccounted for by system operators (Suriyamongkol, 2009). Even in the U.S., where there exists a legacy infrastructure and strong institutions, losses from electricity theft are significant.[27] This suggests that access points are indeed difficult to monitor, even in well-established systems and in well-developed countries.[28] These NTLs can lead unstable power systems to fail or operate sub-optimally as they overload generation units and lead to over-voltage, which then can leave utilities without a true estimate of the quantity of electricity it needs to provide both legal and illegal customers (Depuru et al., 2011).[29]

While the first argument for electricity being non-excludable applies to all four components of the electricity service bundle, similar logic related to tracking voltage and frequency requirements supports the second reason that electricity is non-excludable: it is difficult to monitor appropriated services even to legal customers, where services here refer to voltage and frequency requirements. Voltage and frequency are impacted directly by changes in load caused by others' consumption, and thus NTLs that are impossible to track yet impact the voltage and frequency conditions on the shared network make it difficult to ensure appropriate voltage and frequency levels to all consumers in real-time. Since electricity cannot be stored economically today, supply and demand must always be in real-time balance in order to function appropriately, and relying upon only data from end-use meters and substations leaves system operators blind to the actual operating conditions on distribution lines. As

[26] NTLs, however, exist in most regions of the world and are not strictly a function of country wealth. Lower GDP per capita appears to be associated with higher electricity losses, but there are exceptions. For instance, there are cases where GDP per capita is low but losses related to poor reliability are also low (Millard and Emmerton, 2009).
[27] In the U.S., electricity theft has been estimated to cost billions of dollars annually (Nesbit, 2000). American Electric Power (AEP), which covers about 200,000 square miles across eleven states as the largest investor-owned utility in the U.S., has indicated that its revenue protection-related billings (which are determined based on theft estimates from power system analysis software) exceed $3.2 million annually (Suriyamongkol, 2009).
[28] Suriyamongkol (2009) shows how today's power system analyses tools cannot even capture *known* NTLs let alone those that are not known, which is necessary for balancing loads and ensuring adequate voltage levels and frequency for providing reliable power. Meter readings can help to detect some tampering with equipment and perhaps prevent some electricity theft, but meter data analytics techniques alone are only effective in identifying roughly 30% of power theft (EPRI, 2001).
[29] When NTLs are especially high, they can "trip" generation units and interrupt power supply (Sullivan, 2002). In order to maintain the system's voltage near design level, generators must provide reactive power or else electricity equipment owned by customers, such as computers and refrigerators, will be damaged (Toomey et al., 2005). With multiple customers served simultaneously by a wired network and receiving the same voltage, any individual's action has an impact on voltage levels. When voltage drops, generators produce excess power, which leads all generators connected to the system to spin faster. This increases the frequency of the network and excess energy is absorbed by the rotational energy contained in generators and turbines. Deviations from the design frequency of generators can cause extremely expensive damage, such as turbine blades spinning off their shafts (Toomey et al., 2005). This can lead systems to shut down.

such, the electric power network creates a system where customers consume a shared overall level of reliability in which it is impossible to exclude consumers from its benefits.[30]

As such, the shared nature of frequency and voltage services, which are required for maintaining system reliability, make them susceptible to the collective action of individuals. This is the underlying motivation for our study of how individual firm behavior could, in aggregate, impact the larger shared system.

[30] This is because the transmission of electricity through networks follows the way of lease electrical resistance (i.e., loop flows of electric power), imposing mutual restrictions to users (Künneke and Finger, 2009).

Appendix B: Supporting Tables

Table B1: Summary Statistics of Key Variables (Full Dataset)

	Number of Obs.	Mean	Standard Deviation	Min	Max
Reliability Measures					
Outages (monthly avg.)	40,522	12.15	26.1	0	600
Losses (% of total sales)	24,424	7.375	11.56	0	100
Bribery in Electricity Sector					
Propensity to Bribe	12,154	0.137	0.343	0	1
Firm-Level Controls					
Working Capital (% internal)	60,272	69.33	34.67	0	100
Public (indicator)	71,820	0.0585	0.235	0	1
Percent Private	71,110	89	29.22	0	100
Generator Ownership (indicator)	51,495	0.291	0.454	0	1
Sales (annual) (LCUs)	64,499	7.41E+10	1.12E+13	0	2.70E+15
Country-Level Controls					
GDP per Capita	70,500	10,066	6,977	568.6	29,321
Population Density	72,617	107.9	176.4	1.72	1,125
Inflation (%)	67,839	6.37	5.691	-2.41	34.7
Government Indicator Average	72,617	-0.02	0.544	-1.584	1.77

Source: World Bank Databases

Table B2: Correlations Between Excluded Instruments and Other Regressors

	Informal Sector Obstacle	Quality Certification	Age of Firm	Female Ownership	Percent Foreign
Informal Sector Obstacle	1.000				
Quality Certification	-0.124	1.000			
Age of Firm	0.105	0.115	1.000		
Female Ownership	0.002	0.052	0.027	1.000	
Percent Foreign	-0.070	0.192	0.038	-0.083	1.000
Working Capital (% internal)	-0.152	0.015	-0.127	-0.008	0.016
Public	-0.011	0.087	0.091	-0.002	0.053
Percent Private	0.076	-0.200	-0.040	0.061	-0.900
Generator Ownership	0.026	0.071	0.098	-0.057	0.116
Log(total annual sales)	-0.057	0.203	0.152	-0.042	0.172
Log(GDP per capita)	-0.004	0.009	0.083	-0.043	-0.078
Log(population density)	-0.042	0.138	-0.013	0.114	0.055
Inflation	-0.049	-0.113	-0.095	-0.058	-0.049
Government Indicator Average	0.224	-0.008	0.321	-0.010	0.045

Table B3: Within-Country Variation of Propensity to Bribe for Electricity Connections

	Mean	Standard Deviation	Minimum	Maximum
Afghanistan	0.357	0.481	0	1
Albania	0.197	0.401	0	1
Angola	0.259	0.440	0	1
Argentina	0.025	0.157	0	1
Azerbaijan	0.300	0.464	0	1
Bahamas	0.133	0.352	0	1
Bangladesh	0.510	0.505	0	1
Belarus	0.079	0.273	0	1
Benin	0.478	0.511	0	1
Bhutan	0.022	0.147	0	1
Bolivia	0.027	0.163	0	1
Bosnia and Herzegovina	0.093	0.292	0	1
Botswana	0.025	0.158	0	1
Brazil	0.078	0.268	0	1
Bulgaria	0.094	0.293	0	1
Burkina Faso	0.192	0.398	0	1
Burundi	0.148	0.359	0	1
Cameroon	0.235	0.428	0	1
Central African Republic	0.214	0.415	0	1
Chad	0.472	0.506	0	1
Chile	0.013	0.115	0	1
China	0.058	0.233	0	1
Colombia	0.035	0.183	0	1
Congo	0.156	0.369	0	1
Costa Rica	0.038	0.192	0	1
Croatia	0.034	0.183	0	1
Czech Republic	0.055	0.229	0	1
DRC	0.534	0.503	0	1
Dominican Republic	0.059	0.237	0	1
Ecuador	0.097	0.297	0	1
El Salvador	0.020	0.140	0	1
Estonia	0.068	0.255	0	1
Ethiopia	0.071	0.260	0	1
Fiji	0.194	0.402	0	1
Fyr Macedonia	0.118	0.325	0	1
Gabon	0.200	0.410	0	1
Gambia	0.313	0.468	0	1
Georgia	0.029	0.171	0	1
Ghana	0.333	0.476	0	1
Guatemala	0.049	0.217	0	1
Guinea	0.571	0.499	0	1
Guinea Bissau	0.089	0.288	0	1
Guyana	0.146	0.358	0	1
Honduras	0.094	0.293	0	1

Indonesia	0.286	0.454	0	1
Iraq	0.319	0.468	0	1
Kazakhstan	0.171	0.379	0	1
Kenya	0.277	0.449	0	1
Kosovo	0.091	0.292	0	1
Kyrgyz Republic	0.208	0.415	0	1
Lao PDR	0.283	0.455	0	1
Latvia	0.057	0.233	0	1
Lesotho	0.150	0.362	0	1
Liberia	0.444	0.527	0	1
Lithuania	0.026	0.162	0	1
Madagascar	0.132	0.343	0	1
Malawi	0.125	0.342	0	1
Mali	0.326	0.471	0	1
Mauritania	0.420	0.499	0	1
Mauritius	0.029	0.169	0	1
Mexico	0.079	0.270	0	1
Moldova	0.044	0.208	0	1
Mongolia	0.161	0.369	0	1
Montenegro	0.154	0.376	0	1
Mozambique	0.135	0.347	0	1
Nepal	0.313	0.479	0	1
Nicaragua	0.069	0.254	0	1
Niger	0.148	0.362	0	1
Nigeria	0.384	0.487	0	1
Pakistan	0.683	0.469	0	1
Panama	0.023	0.149	0	1
Paraguay	0.132	0.340	0	1
Peru	0.042	0.200	0	1
Philippines	0.161	0.369	0	1
Poland	0.077	0.270	0	1
Romania	0.053	0.224	0	1
Russia	0.187	0.390	0	1
Samoa	0.208	0.415	0	1
Senegal	0.063	0.243	0	1
Serbia	0.137	0.348	0	1
Sierra Leone	0.063	0.250	0	1
Slovak Repubic	0.045	0.213	0	1
South Africa	0.055	0.229	0	1
Sri Lanka	0.139	0.351	0	1
St. Kitts and Nevis	0.053	0.229	0	1
St. Vincent and Grenadines	0.037	0.192	0	1
Swaziland	0.087	0.288	0	1
Tajikistan	0.329	0.473	0	1
Tanzania	0.217	0.415	0	1
Timor Leste	0.178	0.387	0	1

Togo	0.261	0.449	0	1
Tonga	0.588	0.507	0	1
Trinidad and Tobago	0.047	0.213	0	1
Turkey	0.051	0.220	0	1
Uganda	0.176	0.384	0	1
Ukraine	0.209	0.409	0	1
Uruguay	0.017	0.130	0	1
Uzbekistan	0.154	0.376	0	1
Vanuatu	0.149	0.360	0	1
Venezuela	0.052	0.222	0	1
Vietnam	0.233	0.424	0	1
Yemen	0.410	0.498	0	1
Zambia	0.024	0.156	0	1
Zimbabwe	0.222	0.428	0	1

Table B4: Pseudo-Panel Summary Statistics, Outages Specifications

	Observations	Mean	St. Deviation	Min	Max
Propensity to Bribe	302	0.0837	0.200	0	1
Monthly Outages	302	5.863	14.23	0	120
Log(GDP per capita)	302	5.259	2.502	1.143	10.06
Log(population density)	302	2.372	1.364	0.488	6.113
Inflation	302	3.795	4.349	0.273	30.55
Government Indicator Average	302	-0.252	0.379	-1.765	1.215
Generator Ownership	302	0.229	0.309	0	1
Internal Working Capital (% of total)	302	39.62	28.57	0	100
Public Ownership	302	0.0422	0.166	0	1
Percent Private	302	52.42	30.65	0	100
Log(annual sales)	302	10.25	5.220	2.187	26.50

Table B5: Pseudo-Panel Summary Statistics, Commercial Losses Specifications

	Observations	Mean	St. Deviation	Min	Max
Propensity to Bribe	239	0.122	0.271	0	1
Losses (% of total sales)	239	4.962	9.960	0	80
Log(GDP per capita)	239	6.293	2.538	1.415	10.06
Log(population density)	239	2.776	1.415	0.511	6.113
Inflation	239	4.130	4.104	0.299	28.19
Government Indicator Average	239	-0.266	0.435	-1.326	1.215
Generator Ownership	239	0.291	0.362	0	1
Internal Working Capital (% of total)	239	46.62	31.92	0	100
Public Ownership	239	0.0486	0.186	0	1
Percent Private	239	61.29	32.14	0	100
Log(annual sales)	239	12.37	5.452	2.360	26.50

Table B6: Pooled OLS Instrumental Variables Regression Results – Monthly Power Outages

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Propensity to Bribe	**18.13****	**19.49*****	**15.31****	**15.68****	**16.64****	**14.27****	**14.83****	**14.79****	**15.05****	**20.51****
	(8.461)	**(7.131)**	**(6.407)**	**(6.416)**	**(7.544)**	**(6.086)**	**(6.623)**	**(6.627)**	**(6.813)**	**(9.294)**
Working Capital (% internal)		-0.00912	-0.0103	-0.00978	-0.00975	-0.0123	-0.0155**	-0.0155**	-0.0156**	-0.0157*
		(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Generator Ownership (dummy)			0.871*	0.851*	0.800*	1.093*	1.092*	1.094*	1.189*	1.065
			(0.497)	(0.492)	(0.441)	(0.629)	(0.662)	(0.662)	(0.670)	(0.701)
Public Ownership (dummy)				1.230	1.172	1.354	1.337	1.336	1.326	1.286
				(1.556)	(1.603)	(1.846)	(1.854)	(1.855)	(1.869)	(1.941)
Private Ownership (%)					-0.00654	-0.00676	-0.00795	-0.00794	-0.00735	-0.00573
					(0.0100)	(0.00945)	(0.00999)	(0.00999)	(0.0100)	(0.0105)
Log (total annual sales)						-0.181	-0.155	-0.156	-0.163	-0.151
						(0.166)	(0.171)	(0.172)	(0.173)	(0.177)
Log (GDP per capita)							-6.546	-4.230	-3.247	-8.223
							(14.87)	(11.97)	(11.61)	(13.49)
Log (population density)								-19.43	-21.88	-16.98
								(19.36)	(18.91)	(24.86)
Inflation									0.0815	0.0376
									(0.362)	(0.465)
Government Indicator Average										-5.949*
										(3.266)
Observations	3,567	2,813	2,504	2,499	2,499	2,234	2,118	2,118	2,106	2,106
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B7: First Stage Regression Results - Pooled OLS - Monthly Power Outages

	Coefficient	St. Error	p-value
Working Capital (% internal)	0.000	0.000	0.580
Generator Ownership	0.034 *	0.018	0.067
Public	0.009	0.036	0.810
Percent Private	0.000	0.001	0.437
Log(total annual sales	-0.001	0.004	0.861
Log(GDP per capita)	0.277	0.508	0.588
Log(population density)	-0.947	0.940	0.318
Inflation	0.000	0.019	0.993
Government Indicator Average	0.168 **	0.078	0.035
Informal Sector Obstacle	0.019 ***	0.006	0.002
Quality Certification	-0.004	0.020	0.840
Age of Firm	-0.001 ***	0.000	0.007
Female Ownership	0.000	0.018	0.992
Percent Foreign	0.000	0.001	0.492
No. of Observations	2106		
F-test of excluded instruments	6.05		

*** p<0.01, ** p<0.05, * p<0.1

Table B8: Pooled OLS Instrumental Variables Regression Results – Commercial Losses Due to Power Outages (% of total sales)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Propensity to Bribe	**14.03***	**20.32***	**25.16****	**26.27****	**29.43****	**28.90*****	**27.83*****	**28.06*****	**29.03*****	**28.29****
	(8.334)	**(11.42)**	**(10.50)**	**(10.69)**	**(11.71)**	**(10.04)**	**(10.10)**	**(10.19)**	**(10.64)**	**(12.41)**
Working Capital (% internal)		-0.0156	-0.0202	-0.0165	-0.0159	-0.0222	-0.0262	-0.0265	-0.0260	-0.0264
		(0.010)	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)
Generator Ownership (dummy)			-2.708***	-2.541***	-2.666***	-1.577*	-1.793*	-1.801*	-1.573*	-1.564*
			(0.884)	(0.873)	(0.951)	(0.902)	(0.915)	(0.919)	(0.890)	(0.873)
Public Ownership (dummy)				4.260	4.239	4.616	4.673	4.653	4.714	4.720
				(3.004)	(2.971)	(2.899)	(2.877)	(2.882)	(2.947)	(2.957)
Private Ownership (%)					-0.0145	-0.0104	-0.00933	-0.00889	-0.00858	-0.00830
					(0.0168)	(0.0143)	(0.0147)	(0.0147)	(0.0152)	(0.0151)
Log (total annual sales)						-1.017***	-1.045***	-1.040***	-1.040**	-1.047**
						(0.373)	(0.394)	(0.395)	(0.409)	(0.409)
Log (GDP per capita)							-21.29	-9.429	-2.918	-3.259
							(49.27)	(53.44)	(57.10)	(57.96)
Log (population density)								-113.8	-112.4	-112.0
								(105.3)	(104.9)	(104.8)
Inflation									-0.679	-0.675
									(1.966)	(2.080)
Government Indicator Average										-0.628
										(4.773)
Observations	1,638	1,321	1,160	1,156	1,156	1,028	980	980	968	968
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B9: First Stage Regression Results - Pooled OLS – Commercial Losses as % of Total Sales

	Coefficient	St. Error	p-value
Working Capital (% internal)	0.000	0.000	0.597
Generator Ownership	0.007	0.022	0.764
Public	0.000	0.030	0.992
Percent Private	-0.001	0.001	0.656
Log(total annual sales	0.000	0.007	0.953
Log(GDP per capita)	-0.693	0.650	0.292
Log(population density)	-0.205	0.902	0.821
Inflation	0.042 **	0.019	0.034
Government Indicator Average	0.237	0.145	0.109
Informal Sector Obstacle	0.020 ***	0.007	0.006
Quality Certification	0.010	0.026	0.689
Age of Firm	-0.001 **	0.001	0.018
Female Ownership	-0.017	0.024	0.476
Percent Foreign	-0.001	0.001	0.664
No. of Observations	968		
F-test of excluded instruments	4.02		

*** p<0.01, ** p<0.05, * p<0.1

Table B10: First Stage Regression Results - Pseudo-Panel IV Regressions on Outages

	Coefficient	St. Error	p-value
Working Capital (% internal)	0.002	0.001	0.074
Public	-0.217	0.130	0.106
Percent Private	-0.011	0.005	0.034
Generator Ownership	0.357	0.116	0.005
Log(total sales)	-0.036	0.017	0.045
Log(GDP per capita)	0.153	0.057	0.012
Log(population density)	-0.019	0.040	0.650
Inflation	-0.003	0.029	0.930
Government Indicator Average	-0.146	0.111	0.201
Informal Sector Obstacle	0.028	0.029	0.352
Quality Certification	0.053	0.098	0.591
Age of Firm	-0.003	0.003	0.371
Female Ownership	0.078	0.087	0.379
Percent Foreign	-0.011	0.005	0.029
No. of Observations	302		
F-test of excluded instruments	3.64		

*** p<0.01, ** p<0.05, * p<0.1

Table B11: First Stage Regression Results - Pseudo-Panel IV Regressions on Commercial Losses

	Coefficient	**St. Error**	**p-value**
Working Capital (% internal)	0.002	0.001	0.269
Public	-0.112	0.194	0.572
Percent Private	-0.003	0.008	0.719
Generator Ownership	0.079	0.151	0.609
Log(total sales)	-0.051	0.021	0.029
Log(GDP per capita)	0.146	0.091	0.130
Log(population density)	-0.055	0.048	0.267
Inflation	-0.070	0.035	0.062
Government Indicator Average	-0.432	0.122	0.003
Informal Sector Obstacle	0.041	0.030	0.193
Quality Certification	0.275	0.123	0.041
Age of Firm	-0.001	0.004	0.880
Female Ownership	0.202	0.088	0.036
Percent Foreign	-0.003	0.008	0.681
No. of Observations	239		
F-test of excluded instruments	3.6		

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B12: Full Dataset Version of Pooled OLS IV Results – Monthly Power Outages

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Propensity to Bribe	**18.36****	**20.17*****	**15.93****	**16.29****	**17.27****	**15.16****	**15.77****	**15.73****	**16.05****	**22.01****
	(8.536)	**(7.303)**	**(6.538)**	**(6.548)**	**(7.715)**	**(6.295)**	**(6.863)**	**(6.867)**	**(7.071)**	**(9.753)**
Working Capital (% internal)		-0.00854	-0.00974	-0.00923	-0.00920	-0.0116	-0.0147*	-0.0148*	-0.0148*	-0.0148*
		(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.00810)
Generator Ownership (dummy)			0.845*	0.826*	0.775*	1.058*	1.053	1.055	1.149*	1.005
			(0.485)	(0.480)	(0.432)	(0.615)	(0.647)	(0.647)	(0.655)	(0.689)
Public Ownership (dummy)				1.244	1.182	1.350	1.334	1.332	1.321	1.279
				(1.569)	(1.616)	(1.864)	(1.874)	(1.874)	(1.889)	(1.973)
Private Ownership (%)					-0.00696	-0.00714	-0.00830	-0.00830	-0.00772	-0.00614
					(0.0097)	(0.0092)	(0.0097)	(0.0097)	(0.0097)	(0.0102)
Log (total annual sales)						-0.167	-0.139	-0.140	-0.147	-0.136
						(0.165)	(0.170)	(0.171)	(0.172)	(0.178)
Log (GDP per capita)							-6.535	-4.341	-3.372	-8.534
							(15.05)	(12.21)	(11.90)	(14.08)
Log (population density)								-18.40	-20.74	-15.38
								(19.75)	(19.26)	(25.74)
Inflation									0.0824	0.0381
									(0.372)	(0.483)
Government Indicator Average										-6.104*
										(3.301)
Observations	3,704	2,899	2,590	2,585	2,585	2,311	2,195	2,195	2,183	2,183
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B13: Full Dataset Version of Pooled OLS IV Results – Commercial Losses as % of Total Firm Sales

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Propensity to Bribe	**15.10***	**21.17***	**25.88****	**26.97****	**30.11****	**29.92*****	**28.93*****	**29.16*****	**30.32*****	**30.40****
	(8.339)	**(11.58)**	**(10.66)**	**(10.83)**	**(11.88)**	**(10.18)**	**(10.26)**	**(10.35)**	**(10.81)**	**(13.15)**
Working Capital (% internal)		-0.0145	-0.0190	-0.0153	-0.0146	-0.0206	-0.0246	-0.0249	-0.0243	-0.0245
		(0.010)	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
Generator Ownership (dummy)			-2.645***	-2.481***	-2.590***	-1.572*	-1.777**	-1.785**	-1.558*	-1.558*
			(0.856)	(0.845)	(0.916)	(0.880)	(0.892)	(0.896)	(0.869)	(0.872)
Public Ownership (dummy)				4.263	4.263	4.605	4.663	4.642	4.699	4.711
				(3.016)	(2.986)	(2.916)	(2.893)	(2.899)	(2.966)	(2.990)
Private Ownership (%)					-0.0122	-0.00772	-0.00657	-0.00619	-0.00584	-0.00541
					(0.0159)	(0.0136)	(0.0139)	(0.0139)	(0.0144)	(0.0145)
Log (total annual sales)						-0.992***	-1.018***	-1.013***	-1.012**	-1.017**
						(0.368)	(0.389)	(0.391)	(0.405)	(0.406)
Log (GDP per capita)							-19.86	-7.797	-0.932	-0.705
							(48.97)	(53.22)	(56.92)	(57.96)
Log (population density)								-115.9	-114.3	-113.6
								(105.1)	(104.5)	(104.1)
Inflation									-0.710	-0.748
									(1.967)	(2.101)
Government Indicator Average										-1.091
										(5.014)
Observations	1,726	1,390	1,229	1,225	1,225	1,092	1,044	1,044	1,032	1,032
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B14: IV Pseudo-Panel Regressions – Robustness check on grouping

	Outages	Losses
Propensity to Bribe for a Electricity Connection	**45.51 ****	**1.87**
	(20.67)	**(7.39)**
Observations	281	226

Robust standard errors in parentheses; errors are clustered on country
*** p<0.01, ** p<0.05, * p<0.1
Note: Both specifications are instrumented and include firm-level and country-level controls, as well as cohort and year fixed effects.
In these regressions, cohorts are grouped based on sector, firm size, and 'control of corruption' in host country.