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By

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Committee in charge:

Professor Gerard Roland, Chair
Professor Yuriy Gorodnichenko
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Abstract

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This dissertation consists of three essays on economic development in the context of South Asia. In the first essay, I study how power outages impact large scale manufacturing firms. First, I use monthly electricity billing data from large scale manufacturing firms in Pakistan to characterize how these firms respond to interruptions in electricity supply. I show that firms differentially adjust on-grid capacity utilization based on their sensitivities to increases in fuel costs. Next, I incorporate the empirical results into a dynamic model of utilization adjustment and self-generation in response to power outages and estimate structural cost parameters. Finally, I use my estimates to determine the magnitude of cost increases that firms incur. My results suggest that between January 2010 to March 2012, no firm in my sample had a cost increase above 1%. During quarters of high numbers of outages, the cost increases for most firms is below 3%. In my sample, firms in the chemical and textile industries are impacted by power outages more than firms, of similar size, in other industries.

In the second essay, I examine the impact of power outages on the likelihood of manufacturing firm exit. Again, I use proprietary electricity billing data for manufacturing firms in Pakistan to determine the month of exit and merge this with monthly outage data during the period 2009-2012. I find that power outages disproportionately increase the exit probability of small firms (both in the formal and informal sector). For each 100 hours of power outages, the probability of small firm exit increases by over 6%. This result is consistent with existing evidence on the impact of power disruption on various measures of firm health as well as research on the cost impact of outages on large scale manufacturing and suggests that policies which target small firms are more likely to alleviate the detrimental effects of power disruption.

In the third essay, I study how religious holidays impact the incidence of violence between Hindus and Muslims in India and I analyze how violence impacts vote share. By exploiting variation in the timing of religious holidays - because Hindu and Muslim holidays follow Sanskrit and Lunar calendars, respectively - I show that religious holidays and the interaction of Hindu and Muslim holidays positively affect the incidence of violence. Next, I consider the usefulness of violence by studying the electoral effects of violence on vote share. I find that violence before an election is associated with electoral gains.

To my parents and godmother, with love.

Contents

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Chapter 1

Estimating the Cost of Power Outages for Large Scale Manufacturing Firms

1.1 Introduction

In July 2012, approximately 10 percent of the world's population was left without electricity. Hospitals, schools and businesses in Northern India were all affected by one of the largest blackouts in human history. Journalists who covered the story described the sheer scope of the event but many who explored the issue further came upon a simple fact - blackouts are common. The *New York Times* reported, "localized blackouts are so common that many businesses, hospitals, offices and middle-class homes have backup diesel fuel generators." In fact, the pervasiveness of blackouts is not unique to India, unreliable electricity supply is a problem throughout the developing world (Aterido et al., 2011; Dethier et al., 2008; Escribano et al., 2010).

Striking evidence of the impact that energy disruptions have on firms can be found in the World Bank's *Enterprise Survey*. Respondents are asked to identify a business environment element from a list that "represents the biggest obstacle faced by this establishment." This list includes elements that have been identified in the economic development literature as having a first order influence on firms: political instability, corruption and financial access. However, business owners and managers in South Asia and Sub-Saharan Africa overwhelmingly choose electricity as the biggest obstacle that they face (Table 2.1). In the Middle East, electricity is cited as 'the biggest obstacle' more often than corruption or financial access. The issue of power disruption becomes even more relevant as projected increases in energy demand come largely from the developing world (Energy Information Administration, 2011). Despite its clear importance, the effect of unreliable electricity supply on firms is an under-researched topic in development economics. In this paper, I analyze how large scale manufacturing (LSM) firm costs are impacted by power outages and find that the effects are minimal.

Due to the variety of deliberate adjustments that firms make, empirically analyzing the effect of energy outages is not straightforward. How a firm is affected depends on exactly what adjustments are made to minimize the disruption. Many firms purchase diesel gener-

Table 1.1: Percentage of firms reporting a business environment element to be the top obstacle

Economy	Financial Access	Corruption	Electricity	Pol Instability
East Asia & Pacific	16.4	6.3	10.2	8.6
Eastern Europe/C. Asia	15.3	7.6	7.6	10.0
High-Income OECD	11.1	5.1	3.9	11.9
Latin America	15.0	6.6	8.8	6.4
Middle East	7.7	9.5	13.2	17.3
South Asia	14.3	5.8	28.7	13.4
Sub-Saharan Africa	20.2	6.3	21.4	6.4

2002-2011 Enterprise Survey Data

ators in order to keep production steady during a blackout, as the *New York Times* quote alludes to above. Steinbuks and Foster (2010) use annual data from the Enterprise Survey Database and study the prevalence of self generation in Africa. They find that firm size is an important determinant of owning a generator, with the probability of ownership doubling in large firms relative to small ones. They also state that generators increase energy costs by a factor of 3 because the price of self generation using costly diesel fuel is higher than electricity from the grid.

Another way that firms can choose to respond to an unreliable energy supply is to self generate a significant proportion of their electricity independently or go off the grid completely. Captive power generation occurs when a firm produces power independently and in an environment of constant power disruption, many firms (especially export oriented ones) choose to disconnect themselves from the central electricity grid. While acquiring generation capacity is a popular response that firms make, it is certainly not the only one.

Firms can also choose to vary capacity utilization by utilizing capital more intensely as well as having labor work overtime, work additional shifts or change shift timings (Ghaus-Pasha, 2009). The intuition behind these adjustments is clear. A firm can deliberately increase utilization while connected to the electricity grid in order to minimize the cost increases that are associated with using generators during a blackout. Increasing utilization does come with higher costs for machinery repair, maintenance, etc. Unfortunately there is very little work that has been done on utilization responses to power outages.

There are several limitations to the existing literature. First, most studies rely on survey data which may suffer from non-response bias, recall bias, etc. Second, precise power outage data is difficult to obtain and so researchers assume an average level, create a proxy or rely on survey responses. Furthermore, the annual frequency of data that is often used is too low to identify the capacity utilization adjustments that firms have been shown to make (in survey responses) and so empirical models may imprecisely estimate the true impact of power disruption. Finally, the fundamental difference between large scale and small/medium scale firms is rarely made explicit. This omission can lead to misconceptions involving how firms are affected by power outages. Large firms are substantially more likely to have generators and excess capacity in order to adjust to outages, as discussed above. These factors lead to smaller increases in cost and much lower losses in output (if any) than the cost increases and losses in output of smaller firms. Lee et al. (1996) note that the 'chief impact of output reduction necessarily falls on small firms.' Furthermore, factory shut downs, which are forced on small firms during outages, lead to significant cost increases which are due to spoilage, machinery breakdown, labor costs, etc. When surveys take the average increase in costs or the average loss of output, the results mix these fundamentally different classes of firms.

To illustrate the point, consider a survey in Pakistan in which firms were asked to detail the increase in the cost of production as a result of power outages (Siddiqui et al., 2011). The average increase in the cost of production for firms in the chemical industry is reported to be a sizable 43.5%. However, looking at the distribution of responses and not simply the average gives a more precise description of cost increases. More than half of chemical firms (most likely the largest firms although this is not reported in the article) responded with an increase in cost below 10% while approximately one third of firms responded with an increase in cost above 50%. Clearly, the impact of power disruption is fundamentally different for firms in their sample and aggregating the responses can be misleading. In this paper, I focus on LSM firms to estimate the cost impact of outages more precisely.

First, I study how firms adapt to an environment of frequent outages. I merge a unique dataset of monthly electricity consumption of firms in Karachi, Pakistan with LSM firm balance sheet and power outage data to address the concerns above. The Pakistan Ministry of Finance's annual *Economic Survey* notes that LSM firms 'dominate the overall sector' in manufacturing output(Rehman, 2010) and so analyzing how these firms are impacted by energy shortages is a prime concern. Using electricity consumption as a proxy for on-grid capacity utilization, I find strong evidence that these firms respond to unscheduled electricity disruptions by managing utilization. In months with frequent power outages, firms bunch production when access to grid electricity is available; and firms with relatively high energy costs as a proportion of total costs (presumably these firms are more vulnerable to electricity disruptions) increase on-grid utilization more than firms with low energy costs as a proportion of total costs. I argue that this *differential* response to outages using capacity utilization is an important result that characterizes how firms adapt to their environment. Because production smoothing is the optimal cost minimizing decision, the deliberate decision to bunch production is consistent with the literature on production decisions under non-convex costs (Hall, 2000). Unfortunately, by estimating only a differential response of firms to outages, I am unable to provide a level estimate of the aggregate cost increase caused by electricity shortage.

In order to estimate the increase in total cost for LSM firms, I build a static model in which firms face power outages, have access to generators and can vary both on-grid and off-grid capacity utilization. Given a production target and a known number of outages in a period (I relax this assumption in the dynamic model), a firm chooses two levels of utilization (on-grid and off-grid) in order to minimize total cost. The firm chooses higher levels of on-grid utilization than off-grid utilization because the cost of production during an outage is greater than the cost of production when connected to the grid. The difference in utilization levels is a function of sensitivity to energy costs, the number of outages in the period and the relative cost of production bunching. In periods without outages, the model gives the standard production smoothing result. This simple model demonstrates that standard economic tools can be used to rationalize the empirical result above.

Next, I incorporate the intuition of the static model into a more realistic dynamic model. To my knowledge, this is the first dynamic, structural model of firm responses to power outages. In the dynamic model, a firm begins each period with a stock of inventories. An expectation of the period's outages is formed and, given a production target, optimal levels of on-grid and off-grid utilization are chosen. If the true number of outages is higher than expected, the firm will underproduce and so it will tap into its stock of inventories to make up for the difference. On the other hand, if the true number of outages is lower than expected, the firm will add to its stock of inventories.

I estimate cost parameters of the dynamic model via simulated GMM and estimate the cost of an LSM firm that suffers from power disruptions and the counterfactual cost associated with no disruptions. This allows me to characterize the percentage increase in cost that is associated with power disruption. Over the period of January 2010 - March 2012, the average percent increase in costs for each of the firms in my sample is less than 1%. Because firms did not suffer from outages during a significant part of 2010, I also report the highest quarterly increase that a firm faces in my sample. When high demand coincides with a high number of outages, I show that the quarterly percentage increase in cost can be as high as 9.7% although most firms in my sample do not have a quarterly percentage cost increase above 3%. My results indicate that there is significant variation in firm cost increases across industries, even among the electricity intensive industries, because power outages are less likely to impact industries with low energy cost shares (e.g. motor vehicles and machinery consume large amounts of electricity but do not have high fuel costs as a proportion of total costs compared to firms in the chemical industry). Therefore, the cost increases for firms in the chemical industry are higher than cost increases for similar sized firms in the motor vehicle and machinery industries.

The broad result that LSM firms are only moderately affected by electricity disruptions helps to inform the discussion of the 'missing middle' (Tyler and Oppenheim, 1986; Tybout, 2000). Researchers have proposed several possibilities why the firm size distribution in developing countries is often comprised of a large number of small firms, relatively few medium sized firms and a small number of large firms (which produce the majority of output). Among these reasons include policies that explicitly favor large firms such as investment incentives and tax breaks as well as de facto advantages like access to credit due to large firms' relatively low risk. In this paper, I note that my results are consistent with an alternative explanation for the missing middle in which large firms are insulated from energy shocks relative to small and medium sized firms. Therefore, a driver of the firm size distribution in the developing world may not simply be preferential treatment of large firms but also the ability of large firms to adjust to, and minimize, the effects of negative shocks such as energy shortages.

This paper is similar to recent work that analyzes the costs of blackouts in China (Fisher-Vanden et al., 2012). The authors create an annual measurement of electricity scarcity, which they argue is a proxy for power outages, and then use annual firm level data to estimate translog cost and value share equations to characterize the cost of blackouts which affected China in the early 2000s. They find that the overall effect of blackouts was to increase production costs by 2%-20%. There are three crucial differences between this analysis and my paper. First, I make an explicit distinction between LSM firms and small/medium sized firms in order to estimate more precise effects for large firms. Second, I build a structural model which allows for firms to adjust capacity utilization in response to power outages. Third, I use precise blackout data as well as monthly electricity consumption and quarterly balance sheet data to estimate percentage cost increases.

This paper builds on the survey based research which analyzes several topics related to power disruption (Baarsma and Hop, 2009; Sullivan et al., 1997; Hallward-Driemeier and Stewart, 2004). I use the evidence of firm adjustment and differential cost increases to inform my analysis. My paper extends this work by providing empirical evidence of utilization adjustment as a response to power outages and structural estimation of cost increases for LSM firms.

My paper draws on the tools that researchers use to model plant level choices of capacity utilization. Hall (2000) studies high frequency data from eleven automobile assembly plants and incorporates the non-convexities in the cost structure, due to labor contracts, into a dynamic model to study capacity utilization and production bunching. Chesnes (2009) builds a dynamic model of US oil refineries in which capacity utilization changes are caused by changes in the price of crude oil. My work is the first to use these insights to analyze firm responses to electricity disruptions and then to incorporate these responses into a dynamic model to estimate the impact of outages. I am also unaware of any other work that uses electricity usage, at the firm level, as a proxy for capacity utilization.[1]

The remainder of this paper is organized as follows. In section 2, I provide an overview of the history of power outages in Karachi. I describe my data in section 3. In section 4, discuss my empirical strategy and then run regressions to establish the relationship between power outages and capacity utilization. Section 5 provides a static model. Section 6 builds the dynamic model and estimates the cost parameters. Section 7 concludes.

1.2 Background

Power Outages in Karachi

Electricity demand grew gradually since Pakistan's independence in 1947 due to urbanization, industrialization and rural electrification. By the 1990s, demand had increased beyond generation capacity to the point that compulsory power outages were necessary (Siddiqui et al., 2011). In 1993 the government established an Energy Task Force that recommended privatizing the energy sector and providing incentives to attract foreign investment. These recommendations led to the establishing of independent power producers (IPPs) which now

[1] Costello (1993) uses annual electricity consumption at the industry level across countries as a measure for capital input.

Table 1.2: Percentage of firms reporting a business environment element to be the top obstacle in Pakistan

Sector	Financial Access	Corruption	Electricity	Pol Instability	N
Food	1.1	10.1	64.7	1.8	125
Textiles	0.4	3.2	87.7	1.0	192
Chemicals	0.0	8.3	68.2	0.0	20
Machinery	7.3	10.9	71.2	0.2	47
Other Man.	5.8	18.4	57.7	0.8	274

2007 Enterprise Survey Data

account for about 25 percent of generation capacity as well as to the privatization of KESC, Karachi's electricity provider, in 2005 (Shoaib, 2012).

Unfortunately the alleviation of energy shortages was short-lived due to the unprecedented growth in the demand for electricity (over 7 percent per year) during past decade (2000-2010) without a corresponding increase in generation capacity (Asif, 2011). According to Karachi Electricity Supply Company (KESC) data, firms in Karachi today can face over 100 hours per month without power from the grid. The Enterprise Survey conducted in Pakistan in 2007 shows how dramatically business owners and managers across industries feel constrained by these disruptions (Table 2.2). In addition, local newspapers often quote leading industrialists as saying that electricity outages are severely detrimental to the manufacturing sector (Dawn Newspaper January, 2012; Daily Times Newspaper April, 2012). The Ministry of Finance is unequivocal in its assessment, "During 2011-2012, energy outages in Pakistan continued to be the dominant constraint in its growth" (Shoaib, 2012).

The electricity disruptions in Pakistan today have several causes. Generation capacity fluctuates seasonally with hydro generation dropping during the December-January period due to irrigation requirements on the dams and rainfall patterns. In addition, peak demand is influenced by seasonal fluctuations in residential demand such as air conditioning in the summer.[2] Periodic decreases in the supply of natural gas for KESC's generation has also resulted in lower generation capacity and blackouts (Express Tribune Newspaper, 2009). Finally, fluctuations in the price of fuel and in the amount of electricity supplied by independent power producers (IPPs) can cause shortfalls. In December 2008, KESC changed its policy to exempt the industrial zones from scheduled power outages and so, with a few exceptions, power outages in Karachi's industrial zones are unscheduled.

When outages do occur, firms make several adjustments to operations that researchers within Pakistan have identified. Popular mechanisms include acquiring self-generation capacity and more intensive utilization of capacity (both machinery and work shifts) (Ghaus-Pasha, 2009). Both adjustments cause increases is costs. Self-generation capacity relies on the use of diesel generators and so manufacturing costs increase due to the difference in price between diesel and electricity from the grid, transportation costs, etc.; Pakistani researchers

[2] Electricity consumption is divided between household (46 percent), industrial (29 percent), agricultural (11 percent), commercial (7 percent), bulk supplies (6 percent) and street lights (1 percent). (Khan and Qayyum, 2009)

estimate the cost of diesel to be approximately two and a half times higher (Sheikh, 2008). More intensive capacity utilization is associated with overtime as well as higher repair and maintenance costs (Pasha et al., 1989).

A more dramatic measure that some firms take is to acquire captive power. In Karachi, this refers to firms which have natural gas delivered to power natural gas generators and use power from KESC intermittently to complement their own generation or when there are disruptions in the natural gas supply. In doing so, these firms are (to varying degrees) insulated from disruptions in the electricity supply.

Previous research on the effects of power outages on manufacturing firms focus on two measures - lost production and cost increase. Lost production is a key measure of the impact of power disruptions for small firms without independent generation and/or excess capacity, as discussed in the previous section. In Pakistan, Ghaus-Pasha (2009) note output recovery rates are high for firms with self-generation capabilities (85%) and far lower for firms without self-generation capabilities (27%). Because the recovery rate of 85% does not take into account utilization adjustments, the true recovery rate for LSM firms is likely higher.[3] Due to these reasons, I focus my analysis of LSM firms on cost impacts of electricity shortages.

1.3 Data

A major innovation of this paper is the linking of monthly electricity billing data as a proxy for capacity utilization with quarterly balance sheet data (and fuel price data) in order to analyze firm responses to outage shocks.

The electricity billing data come from KESC, which is the sole provider of electricity in Karachi. This data includes monthly electricity usage in kilowatt hours as well as the monthly charge for all clients in the four main industrial zones of Karachi (Korangi, SITE, Bin Qasim and Landhi) from September 2009 to March 2012.[4] I use these measures to back out the effective price of electricity that each firm is charged. The average monthly electricity consumption for firms in my sample is approximately 1160000 kilowatt hours with an average price of 11 PKR per kilowatt hour. For empirical work in development economics, this is an extremely useful source of accurate, high-frequency, firm-level data.

Data on the price of diesel is taken from *Inflation Monitor*, published by the State Bank of Pakistan (State Bank of Pakistan, 2009). I transform the price of one liter into the price of a kilowatt hour by assuming that 0.4 liters is converted to a kilowatt hour of electricity using a diesel generator. The resulting difference in the price of electricity versus diesel is consistent with Sheikh (2008) finding that the price of diesel is approximately 2.5 times more the price of electricity.

Quarterly financial data come from the Securities and Exchange Commission of Pakistan (SECP) and firm websites. When these sources are unavailable, I rely on press releases that

[3] In discussions with industry leaders and researchers, I find no evidence that power outages cause losses in output for LSM firms.

[4] Billing data for firms in Landhi starts from February 2010

Table 1.3: Summary Statistics

	Variable	Mean	SD	Min	Max
Full Sample	Electricity Usage	1.1×10^6	3.0×10^6	4.0×10^3	1.9×10^7
	Net Sales	9.1×10^5	1.3×10^6	9.8×10^3	6.3×10^6
	Fuel Share	.05	.06	.004	.306
Chemical	Electricity Usage	2.2×10^6	4.6×10^6	12000	1.9×10^7
	Net Sales	8.5×10^5	1.2×10^6	4.4×10^4	5.3×10^6
	Fuel Share	.065	.08	.016	.306
Motor Vehicle	Electricity Usage	6.5×10^5	6.7×10^5	2.4×10^4	2.5×10^6
	Net Sales	1.2×10^6	1.5×10^6	3.5×10^4	6.3×10^6
	Fuel Share	.017	.016	.004	.046

Note Summary statistics. Electricity usage is measured in kilowatt hours and net sales is measured in thousands of PKR. Fuel share is defined as electricity and diesel costs divided by total costs. The chemical industry has higher fuel costs than the average firm in the sample and the motor vehicle industry has a lower fuel costs.

I access through Factiva. This data includes net sales, cost of goods sold, property and plant values, wages and fuel cost. Wage and fuel cost data are only provided in annual financial statements while all other variables are found in the quarterly financial statements.[5] I divide fuel cost by total cost of goods sold to get the fuel share of total cost. I present summary statistics for the main variables in my analysis in Table 1.3. I also include summary statistics for firms in the two industries for which I have the most firms, the chemical industry and the motor vehicle industry. Although both industries are considered to use large amounts of energy, firms in the chemical industry have significantly higher fuel costs as a proportion of total costs.

KESC also provides a detailed list of power outages at the hourly level from September 2009 to March 2012. This data is aggregated to the monthly level for regression analysis. Since December 2008, KESC policy has been to exempt industrial zones from scheduled outages.[6] Therefore, the vast majority of electricity disruptions are unscheduled. The maximum number of hours without power is 216 hours, which occurred in December 2011, while some months in early 2010 were without outages entirely. Load shedding affects all industrial zones identically. I plot the time series variation in figure 2.1.

I restrict the sample to firms that I can match quarterly financial data with client billing data. I match most of the firms based on client name and address.[7] This results in a sample of 45 large, publicly traded manufacturing firms. These firms all have independent generators (based on a reading of quarterly financial statements). Finally, a list of users of

[5]Fuel cost is defined as the amount spent on utility (electricity) charges as well as diesel in a particular year. In cases when press releases are used, I am unable to extract fuel cost data.

[6]In the last quarter of 2011, scheduled outages did occur due to natural gas shortages.

[7]Client data includes client name and address, though in several cases the client name is not the firm name but an employee of the firm. In these cases I try to use the address of the firm to match with balance sheet data. Unfortunately, I cannot match all quarterly financial statements with billing data and most of the unmatched firms are in the textile sector.

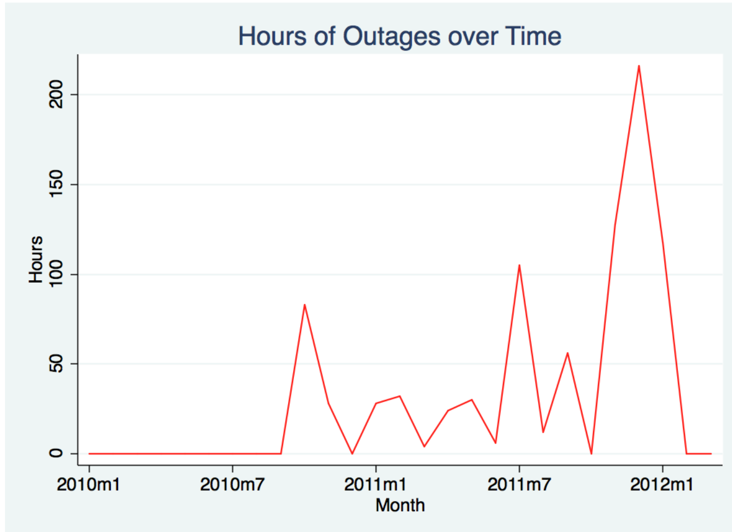

Figure 1.1: **Note** A plot of the number of hours of power outages for industrial clients in Karachi from January 2010 - March 2012.

captive power is provided by KESC[8]; since these firms are insulated from outages, I exclude them from my sample which leads to a sample of 28 firms in 9 industries including textiles, chemicals, machinery, motor vehicles, food and paper.

1.4 Reduced Form Analysis

1.4.1 Intuition

Consider a firm that faces convex costs and an exogenous production target, the standard cost minimizing decision will be to smooth production because any production bunching will lead to higher overall cost. In other words, utilization will be constant over the time period. On the other hand, if a power outage causes costs to discontinuously increase (due to a higher price of energy), it may be beneficial for a manager to increase utilization when the firm is back on the electricity grid - even when there are costs to bunching production. In other words, the manager may choose a higher on-grid utilization rate than the off-grid utilization rate.

One possibility for estimating the effect of power disruptions on utilization is to exploit changes in the monthly number of hours without power. In this case, the idea would be to test if on-grid utilization increases more in the presence of more outages. However, there is one problem with this strategy. There could plausibly be other shocks occurring at the same time that also influence utilization (e.g., changes in the price of other input prices, city-wide

[8]Firms that use captive power have natural gas supplied by the Sui Southern Gas Company (SSGC) which powers natural gas generators in the plant. These firms are affected by interruptions in the supply of natural gas but they are unlikely to be affected by power shortages.

strikes in response to the outage, etc). In this case, identifying the effect of the outage is difficult.

Instead, I use the fact that power outages should differentially affect firms. If anecdotal and survey evidence of cost minimization in response to outages is accurate, we would expect for the increase in on-grid utilization to depend on the price differential between diesel and electricity as well as the vulnerability of a firm to increases in fuel costs. For example, if a firm's fuel cost as a proportion of total cost is high then we would expect for that firm to increase it's on-grid utilization more than a comparable firm with lower fuel costs as a proportion of total cost. Therefore, the effect on utilization should be stronger during periods with more outages, for firms with higher fuel costs and when the price differential between diesel and electricity is large.

As a result, my identification strategy makes use of not only the temporal variation of power outages and the price differential of fuel types but also of the cross-sectional variation in fuel costs (as a proportion of total costs) for each firm.

1.4.2 Electricity Consumption as a Proxy for Utilization

Capacity utilization refers to the intensity with which the resources of the firm are employed (per unit of time). My assertion is that this intensity is captured by amount of electricity that a firm consumes in a month, when this is normalized by the number of hours that the firm is connected to the electricity grid. Each of the plants in my sample is dependent on modern machinery and so an increase in the number of work shifts or an increase in the intensity of the use of capital will be picked up in the number of kilowatt hours billed. In addition, because electricity cannot be easily stored, the electricity flow corresponds to the amount used in the production process (Costello, 1993). Note that electricity consumption will only measure utilization while a firm is on the electricity grid and so I normalize the number of kilowatt hours by the amount of time that the firm is receiving electricity in order to create a proxy for the on-grid utilization rate:

$$\begin{aligned} U_{it} &= \frac{Kwh_{it}}{hrs\ on\ grid} \\ &= \frac{Kwh_{it}}{(hrs\ in\ month) - (hours\ of\ outages)} \end{aligned}$$

One potential concern about using the above formulation as a proxy for utilization is the possibility that capacity could be changing over time. For instance, if a firm buys more machinery then an increase in electricity consumption may not be due to an increase in utilization. First, the period that I study does not coincide with significant economic growth in Pakistan and so it is unlikely that systematic expansion is occurring. Second, I observe electricity consumption at a monthly level and so changes in monthly consumption are plausibly associated with changes in utilization rather than buying and selling of the capital stock. Third, re-run my empirical tests using a subsample of firms which have minimal changes in reported capital in the robustness section.[9] Finally, I allow for capacity to change over time in my theoretical model and estimation.

1.4.3 Firm Vulnerability

I incorporate the intuition of empirical strategy into a triple interaction 'vulnerability' term:

$$vulnerability_{it} = outage_t \times log(\frac{P_{D,t}}{P_{E,it}}) \times \frac{FC_i}{TC_i}$$

Here $outage_t$ is the monthly number of hours without power, $P_{D,t}$ and $P_{E,it}$ are the power of diesel and electricity, respectively, and $\frac{FC_{it}}{TC_{it}}$ is the fuel cost divided by total cost for a firm i. Because the price of diesel is always higher than the price of electricity, $log(\frac{P_{D,t}}{P_{E,it}})$ is always positive. As stated above, the fuel cost data comes from annual financial statements and so I take the 2010 fuel cost and divide it by the total cost of goods sold for 2010 to get this ratio.

1.4.4 Empirical Result

I analyze the variation in firm utilization with the following specification:

$$log(U_{it}) = \beta_0 + \beta_1 log(Y_{i,Q_t}) + \beta_2 log(\frac{P_{D,t}}{P_{E,it}}) + \beta_3 vulnerability_{it} + \eta_t + \psi_i + \epsilon_{it} \tag{1.1}$$

Here U_{it} is a proxy for on-grid utilization (defined above) for firm i in month t. Much of the variation in the utilization proxy should be caused by a changing demand for electricity, which in turn, should be a caused by changing production targets. Because I do not directly observe each firm's production targets, I include (log) net sales for the quarter, Y_{i,Q_t}, as a proxy. Month fixed effects in this regression, η_t, control for systematic differences in utilization each month that do not depend on firm vulnerability; these can include the effects of flooding, city-wide strikes and holidays. Firm fixed effects, ψ_i, control for systematic differences in utilization across firms for all periods. Finally, $log(\frac{P_{D,t}}{P_{E,it}})$ controls for on-grid utilization changes that are caused only by the percentage price differential in energy. Note $P_{D,t} > P_{E,it}$ for all firms and time periods.

The coefficient of interest is β_3. The results of this estimation are reported in Table 1.4. In the first column, I include net sales, firm fixed effects, $log(\frac{P_{D,t}}{P_{E,it}})$ and the number hours of outages in a month divided by 100 (to scale the coefficient). The coefficient estimated on net sales is positive though insignificant. The positive estimate is consistent with firm utilization

[9] I use the balance sheet variable 'property, plant and equipment' as a proxy for capital.

Table 1.4: Effect of Outages on Firm Utilization

	(1) $log(U_{it})$	(2) $log(U_{it})$	(3) $log(U_{it})$
$log(Y_{iQ_t})$	0.074	0.178***	0.082*
	(0.06)	(0.05)	(0.04)
$log(U_{i,t-1})$			0.297***
			(0.04)
$vulnerability_{it}$	0.085**	0.084**	0.096***
	(0.04)	(0.04)	(0.03)
$log(\frac{P_{D,t}}{P_{E,it}})$	0.444**	1.052***	0.974***
	(0.18)	(0.35)	(0.33)
$Outage_t$	0.002		
	(0.03)		
Firm FE	Y	Y	Y
Month FE		Y	Y
R^2	0.972	0.980	0.983
N	734	734	701

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
standard errors clustered at firm level

being driven by production targets however without time fixed effects this coefficient is not differentiable from zero. The coefficient on the percentage change of the difference between diesel and electricity is positive and significant. This is consistent with firms responding to percent changes in the relative price of energy when choosing utilization levels. Finally, the coefficient of interest is positive and significant. The estimate of 0.085 suggests that an additional 100 hours of outages will increase on-grid utilization by 8.5%.

In column 2, I include monthly fixed effects which absorb the outage variable. The vulnerability interaction term described above is positive and significant. This is strong evidence that firms manage utilization in order to minimize the cost increases which result from power disruptions. As a robustness check I include lagged utilization, U_{it-1}, in column (3). Although net sales should be a good indicator of production targets across quarters, there is also within-quarter variation in utilization. Therefore, I also include lagged utilization, U_{it-1}, in order to account for within-quarter variation. As expected, the lagged utilization variable is positive and significant and the inclusion of lagged utilization increases the R^2. In this specification, the coefficient of interest continues to be positive and significant.[10]

1.4.5 Robustness

My motivation for the regressions above is based on a firm making the decision to increase on-grid utilization during a period of frequent outages and to decrease off-grid utilization in order to minimize cost increases. A consequence of this reasoning is that power outages,

[10]As stated above, I address the potential concern that capacity does is changing during the time period in the robustness section by re-running the empirical specification for firms that have minimal changes in reported capital and by including (log) capital as an additional regressor.

on average, should increase utilization *and* decrease the total consumption of electricity.[11] In columns (1) and (2) of table 1.5, I show that this is the case. In column (1), I test the following specification:

$$log(E_{it}) = \beta_0 + \beta_1 log(Y_{i,Q_t}) + \beta_2 log(E_{i,t-1}) + \beta_3 Outage_t + \psi_i + \epsilon_{it} \tag{1.2}$$

Here, E_{it} is total electricity consumed for firm i at time t. I include lagged electricity consumed in the regression as a proxy for inter quarter production targets as in the main specification. The coefficient of interest is β_3, which is negative and significant. Therefore it is the case that outages cause a decrease in aggregate consumption of electricity. In column (2), I test a specification analogous to the specification in (1) and show that utilization increases on average during months with frequent power outages.

Another potential concern is the possibility that my results are being driven by one industry. In columns (3) and (4) I drop firms from the chemical and motor vehicle industries, respectively, as they are the industries with the most firms in my sample. My main results continue to be significant. Finally, a potential concern could be that capacity may be changing during the time period of September 2009 - March 2012, if this is the case then electricity consumption may not be a good proxy for capacity utilization. I address this in two ways. In column (5), I explicitly include the common measure for capital from firm balance sheets, 'property, plant and capital.' In column (6), I restrict my sample to firms which only deviate from the firm's average level of 'property, plant and capital' by 20% and re-run my specification. In both cases, my results continue to be significant.

1.5 A Static Example

The results above suggest active adjustments by firms in order to minimize cost increases brought on by power outages. I now build a simple model which consistent with the above results. The rest of this section describes the model.

1.5.1 Quadratic Costs

Following Chesnes (2009), assume the following per-period production cost specification:

$$C_{it}(u_{it}; P_{Energy,it}, q_{it}) = \gamma_0 q^*_{it} + \gamma_1 q^{*2}_{it} + \gamma_2 q^*_{it} P_{Energy,it} \tag{1.3}$$

where C_{it} is the firm i's cost in period t. Cost is a function of capacity q_{it}, utilization u_{it} and the price of energy $P_{Energy,it}$. The output in any period is the product of the utilization level and capacity, $u_{it}q_{it} = q^*_{it}$. The quadratic term in the production function γ_1 imposes increasing marginal costs and, more importantly, imposes a cost to production bunching.[12]

[11] If the total consumption of electricity does not decrease, it would suggest that firms are not using generators when off the grid.

[12] Note with a linear cost structure there is no cost to production bunching.

Table 1.5: Robustness Results

	(1) $log(E_{it})$	(2) $log(U_{it})$	(3) $log(U_{it})$	(4) $log(U_{it})$	(5) $log(U_{it})$	(6) $log(U_{it})$
$log(Y_{i,Q_t})$	0.075*	0.080*	0.085*	0.046	0.082*	0.035
	(0.04)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)
$log(E_{i,t-1})$	0.400***					
	(0.04)					
$log(U_{i,t-1})$		0.334***	0.257***	0.309***	0.299***	0.239***
		(0.03)	(0.03)	(0.05)	(0.04)	(0.02)
$Outage_t$	-0.070***	0.054**				
	(0.02)	(0.02)				
$vulnerability_{it}$			0.078**	0.097***	0.100***	0.057**
			(0.03)	(0.03)	(0.03)	(0.03)
$log(\frac{P_{D,t}}{P_{E,it}})$			1.089***	1.257**	1.038***	1.676***
			(0.40)	(0.40)	(0.33)	(0.37)
$log(K_{i,Q_t})$					0.024	
					(0.08)	
Firm FE	Y	Y	Y	Y	Y	Y
Month FE			Y	Y	Y	Y
R-sqr	0.977	0.975	0.978	0.986	0.983	0.989
dfres	744	744	454	565	659	411

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

In addition, the cost of production bunching is increasing in output which incorporates increasing costs as a firm nears its capacity constraint. The term γ_2 incorporates a sensitivity to the price of energy. When the firm is connected to the electricity grid the price of energy is the price of electricity, $P_{Energy} = P_E$, and similarly when the firm is off the grid the price of energy is the price of diesel $P_{Energy} = P_D$.

1.5.2 Outages

Suppose a firm faces T_O periods of power outages and T_G periods connected to the grid, such that $T_O + T_G = T$. Further assume that the firm knows T_O and T_G (I relax this assumption in the next section) and that capacity is fixed at q_{it} over the T periods. Denote off-grid utilization as $u_{O,it}$ and on-grid utilization as $u_{G,it}$. Output during each of the T_O periods will therefore be $u_{O,it}q_{it} = q^*_{O,it}$ and during of the T_G periods will be $u_{G,it}q_{it} = q^*_{G,it}$. Total firm cost over T periods is the following

$$T_O[\gamma_0 q^*_{O,it} + \gamma_1(q^*_{O,it})^2 + \gamma_{2,i}P_{Diesel}q^*_{O,it}] + T_G[\gamma_0 q^*_{G,it} + \gamma_1(q^*_{G,it})^2 + \gamma_{2,i}P_{Electricity}(q^*_{G,it})]$$

A manager will then choose optimal levels of utilization to minimize total cost over T periods, given a production target, $\overline{q}_{it}$:

$$\min_{u_{O,it},u_{G,it}} T_O[\gamma_0 q^*_{O,it} + \gamma_1 (q^*_{O,it})^2 + \gamma_{2,i} P_{D,t} q^*_{O,it}] + T_G[\gamma_0 q^*_{G,it} + \gamma_1 (q^*_{G,it})^2 + \gamma_{2,i} P_{E,it} q^*_{G,it}] \quad (1.4)$$

s.t.

$$T_O q^*_{O,it} + T_G q^*_{G,it} \geq \overline{q}_{it} \quad (1.5)$$

$$T_O + T_G = T \quad (1.6)$$

Because the price of diesel is higher than the price of electricity, the firm manager will choose the on-grid utilization rate higher than the off-grid utilization rate i.e. the manager will choose to bunch production. The solution to the constrained minimization yields the optimal choice of on-grid utilization:

$$u_{G,it} = \frac{\overline{q}_{it}}{T q_{it}} + \frac{1}{2q_{it}}(P_{D,t} - P_{E,it})\frac{T_O}{T}\frac{\gamma_{2,i}}{\gamma_1} \quad (1.7)$$

The first term $\frac{\overline{q}_{it}}{T q_{it}}$ is the per period utilization rate that would be chosen if the firm owner smoothed production over all periods. Note that if there are no outages, $T_O = 0$, or the price of electricity equals the price of diesel, $P_E = P_D$, then this model simplifies to the standard production smoothing model. The second term $\frac{1}{2q_{it}}(P_{D,t} - P_{E,it})\frac{T_O}{T}\frac{\gamma_{2,i}}{\gamma_1}$ denotes how much a firm increases utilization while on the electricity grid. This increase depends on three elements: the price difference between diesel and electricity $(P_{D,t} - P_{E,it})$, the number of periods of outages $\frac{T_O}{T}$ and a sensitivity to changes in the price of energy divided by the cost of production bunching, $\frac{\gamma_{2,i}}{\gamma_1}$. Although the model allows for a manager to shut down the plant during an outage and set $u_{O,it} = 0$, for plausible values of the parameters this will not happen. The above choice of on-grid utilization is consistent with the empirical results in the previous section in which I analyze changes in on-grid utilization with a triple interaction of a firm's fuel price differential, its fuel share costs and the number of hours of outages.

1.6 The Dynamic Model

The discussion in the previous section provides intuition about a plant manager's decision to bunch production without formally introducing a multi-period model. One unrealistic element in the model above is the assumption that a manager knows the number of outages in the current period. A more realistic assumption would be that the manager forms an expectation of the number of outages and chooses on-grid and off-grid utilization based on this expectation. Although this assumption is plausible, it also leads to the question of what happens when the number of outages is realized. If the manager's expectation of outages turns is higher than the true number of outages then the firm will overproduce and vice versa. When the firm overproduces, I assume that it stores the excess output in inventories; whereas when the firm underproduces, I assume that it takes the difference between the target and the amount produced from inventories. This can be formulated as the dynamic program below

$$V(s,T_O,T_G) = \min_s E[T_O|\Omega][\gamma_0 u_O q + \gamma_1 (u_O q)^2 + \gamma_2 P_D u_O q] + E[T_G|\Omega][\gamma_0 u_G q + \gamma_1 (u_G q)^2 + \gamma_2 P_E u_G q] + \beta E_{T'_O,T'_G|T_O,T_G} V(s',T'_O,T'_G)$$

$$s' = T_O u_O q + T_G u_G q + s - q^* \tag{1.8}$$

$$s, s' \geq 0 \tag{1.9}$$

$$T_{O,t} + T_{G,t} = T \tag{1.10}$$

This can be simplified using (9):

$$V(s,T_O) = \min_s E[T_O|\Omega][\gamma_0 u_O q + \gamma_1 (u_O q)^2 + \gamma_2 P_D u_O q] + \big[T - E[T_O|\Omega]\big][\gamma_0 u_G q + \gamma_1 (u_G q)^2 + \gamma_2 P_E u_G q] + \beta E_{T'_O|T_O} V(s',T'_O)$$

$$s' = T_O u_O q + (T - T_O) u_G q + s - q^* \tag{1.11}$$

$$s, s' \geq 0 \tag{1.12}$$

Here the state variable, s, is the level of inventories, the choice variables are on-grid utilization, u_G, and off-grid utilization, u_O, $E[T_O|\Omega]$ is the expected number of outages and β is the discount factor. (10) is the standard transition equation for the inventories and (11) is a non-negativity condition. Capacity is a Cobb-Douglas function of capital and labor, $q_{it} = k^{1-\alpha} l^{\alpha}$, where q_{it} refers to the capacity of firm i at time t. This formulation links capacity to physical capital and labor and so, over time, if the firm is increasing its stock of these factors then capacity is increasing. In addition, this formulation allows me to indirectly take into account investment; although the firm doesn't explicitly choose investment, if a firm invests and increases its stock of capital, the increased capital will be represented as increased capacity in future periods.

In order to enforce the non-negativity condition on inventories, I replace (11) with a condition that the firm must produce enough to meet the production target if the maximum number of outages occurs:

$$s' + q^* = T_{O,max} u_O q + (T - T_{O,max}) u_G q + s \geq 0$$

1.6.1 Estimation

The dynamic model above can be estimated using the inter-temporal Euler equation or simulation based methods. I choose to use simulated GMM for several reasons. First, I do not directly observe utilization or inventory (electricity consumption data is a proxy for utilization). Second, the cost data that I have for each firm is balance sheet data and reflects the cost of goods sold in the period. At this high level of frequency, 'cost of goods sold' may not reflect the effects of outages contemporaneously if the goods sold come from the stock inventories.

While I assume that the cost parameters γ_0 and γ_1 are constant across firms, inspection of the fuel cost proportions for the firms in my sample demonstrate that γ_2 differs significantly across firms (even firms in the same industry).[13] Therefore instead of estimating γ_2, I calculate it using my balance sheet data. In the model fuel cost can be expressed in the following way:

$$
\begin{aligned}
Fuel\ Cost &= T_O \gamma_{2,i} P_{D,t} q^*_{O,it} + T_G \gamma_{2,i} P_{E,it} q^*_{G,it} \\
&= \gamma_{2,i}(P_{D,t} T_O q^*_{O,it} + P_{E,it} T_G q^*_{G,it})
\end{aligned}
$$

Production in T periods can be written as $\overline{q} = (T_O u_{O,it} + T_G u_{G,it}) q_{it}$. Let $\alpha \in (0,1)$, if we assume that production can be divided between α that is produced while off-grid and $1-\alpha$ that is produced while on-grid, then we can further simplify $\overline{q} = \alpha\overline{q} + (1-\alpha)\overline{q}$ where $\alpha\overline{q} = T_O u_{O,it} q$ and $(1-\alpha)\overline{q} = T_G u_{G,it} q$. A natural choice is $\alpha = \dfrac{T_O}{T}$ because this is an upper bound for α.[14] Using fuel cost data from annual financial statements, I calculate $\gamma_{2,i}$ in the following way

$$
\gamma_{2,i} = \frac{Fuel\ Cost}{P_{D,t}\dfrac{T_O}{T}\overline{q} + P_{E,it}(1 - \dfrac{T_O}{T})\overline{q}}
$$

In order to implement simulated GMM, I make the following standard assumptions. I set $\alpha = 0.3$ and the discount rate, $\beta = 0.95$. I estimate the outage process by assuming that it follows an AR(1) and use Tauchen's method to compute monthly 10-state Markov chains whose sample paths approximate those of the estimated AR(1) process. In addition, I discretize the state space with 15 values which are chosen as Chebyshev interpolation nodes. For each firm/month pair, I iterate the policy function on the actual state (production target, price of diesel, price of electricity) in my sample until convergence and estimate the utilization rate.

For each firm i, I form the following moment:

$$
M_i = \frac{1}{T_i}\sum_t (C_{it} - \hat{C}_{it})
$$

where $\hat{C}_{it}$ is firm i's average cost. Each of these moments is stacked to form the moment

[13] Ideally I would assume that the cost parameters γ_0 and γ_1 vary by industry but unfortunately I do not have enough data to precisely estimate these parameters by industry.

[14] My results are consistent for alternate choices of α

Table 1.6: GMM Estimates - 1 Step

Parameter	Coefficient	Standard Error
γ_0	0.71***	0.04
γ_1	1.1e-06*	5e-07

Note Estimates of cost parameters from 1 step GMM.

Table 1.7: GMM Estimates - 2 Step

Parameter	Coefficient	Standard Error
γ_0	0.74***	0.02
γ_1	4.0e-07	4.1e-07

Note Estimates of cost parameters from 2 step GMM.

vector: $M(\gamma)$. In order to normalize the costs for different firms (so that firms with higher average costs are not weighted more than others) I create a weighting matrix W that simply divides each moment by the firm's average cost (so I am minimizing the percentage difference between a firm's simulated average cost and its actual average cost). I then numerically solve the following problem:

$$Min_{\gamma} M(\gamma)' W^{-1} M(\gamma)$$

I calculate a matrix G of numerical derivatives, where for parameter s and moment t

$$G_{ts} = \frac{M_t(\overline{\gamma}_s) - M_t(\underline{\gamma}_s)}{\gamma_s * 1\%}$$

where $\overline{\gamma}_s$ refers to the parameter γ_s perturbed by 0.5% above the estimate. I calculate the variance-covariance matrix in the standard way.

Because of my limited sample, 2 stage efficient GMM may not give more accurate estimates but I report results in Table 1.6 and 1.7. In 1 step consistent GMM, both coefficient estimates are significant while in 2 step efficient GMM, γ_1 is significant while γ_2 is not. This is potentially due to the small sample or differing γ_2 values across industries but, as mentioned above, my limited sample does not allow for me to test this.

1.6.2 Counterfactuals

An important advantage of structurally modeling the relationship between power disruption and firm cost is the ability to provide counterfactual estimates; in particular, I consider the

Table 1.8: Outage Impacts on Firms of Similar Size in Different Industries

Industry	Total Impact	Largest Quarterly Impact
Chemical	.93%	2.8%
Machinery	0.26%	1.6%
Motor Vehicle	.07%	1.3%

Note Counterfactual analysis. I compare the predicted cost with outages and the counterfactual cost without outages for 3 firms with similar net sales from different industries. The difference in the impact of outages is largely due to differing fuel shares of total cost.

average increase in the cost of firms due to outages during the period of January 2010 to March 2012.

In table 1.8, I compare percentage cost increases for firms of similar size (measured as net sales) in different industries.[15] In column (1), I present the average percentage cost increase for these firms. I find that each of the firms have minimal cost increases over the entire sample period - the largest percentage increase is .98%. However, the firm in the chemical industry has a much higher percentage cost increase relative to firms in the machinery and motor vehicle industries. This is due to the fact that although the machinery and motor vehicle industries generally consume large amounts of electricity, fuel cost as a proportion of total cost is relatively low because raw materials are a larger proportion of total costs. In column (2), I present the highest quarterly percentage increase for these firms. I find that quarterly increases in cost can have moderately large magnitudes with the chemical firm having an increase of 2.8% in the last quarter of 2011.

In table 1.9, I compare percentage cost increases for firms in the chemical industry (the industry with the most firms in my sample). In column (1), I present the average percentage cost increases for these firms over the sample period. Again, I find that the total percentage increases in cost over the two year time span are minimal with a high of .93% and a low of .07%. However, in column (2) I present the highest quarterly percentage increase for these firms and I find that these increases can be large in magnitude. The largest quarterly percentage increase is 9.8% for a firm that faced high demand (production target) in the same quarter as a high number of power outages. Therefore, quarterly percentage increases in cost can vary significantly across firms within an industry. This is largely due to differences in the firms' fuel shares of total cost but also, to a lesser extent, to the correlation between demand and outages.

These counterfactual exercises give valuable insight into the way that power outages affect large manufacturing firms. First, over the full time span, the impact of outages is minimal with most firms in my sample increasing cost by less than 1%. Second, differing fuel costs as a proportion of total cost across industries affect the impact of electricity disruptions more than simply total electricity consumption. Third, within an industry there is significant variation in the cost increases caused by electricity disruptions. Based on my limited sample, the LSM

[15] I do not include a textile firm because my sample does not include a firm of that size.

Table 1.9: Outage Impacts on Firms of Differing Size in the Chemical Industry

Firm	Total Impact	Largest Quarterly Impact
Firm 1	.93%	2.8%
Firm 2	0.38%	2.1%
Firm 3	0.36%	1.1%
Firm 4	0.36%	1.5%
Firm 5	.07%	1.3%
Firm 6	.13%	.95%
Firm 7	.08%	.7%
Firm 8	.69%	1.7%
Firm 9	.85%	9.8%
Firm 10	.38%	2.2%

Note Counterfactual analysis. I compare the predicted cost with outages and the counterfactual cost without outages for 10 firms of differing sizes from the chemical industry. The difference in the impact of outages is due to differing fuel shares of total cost as well as the fact that some firms have high demand during periods of high outages which leads to higher percentage increases in cost.

firms in the chemical and textile industries are impacted by power outages more than LSM firms, of similar size, in other industries.

1.7 Conclusion

The evidence is undeniable that electricity disruption is one of the most important constraints that firms face in the developing world. Unfortunately, mainstream development economics has provided few insights into the adjustments that firms make and the impact that they face. This paper is an attempt to address both topics. First, I argue that generators as well as excess capacity allow LSM firms minimize the increases in cost associated with power outages. I empirically demonstrate that these firms do adapt to their environment by varying capacity utilization using the monthly electricity billing data for a sample of 28 firms in Pakistan. Specifically, I show that firms choose higher levels of on-grid utilization (than off-grid utilization) because the cost of production during an outage is greater than the cost of production when connected to the grid; and the magnitude of the increase in on-grid utilization is directly related to the sensitivity of a firm's total cost to changes in energy cost, the number of outages in the period and the relative cost of production bunching.

I incorporate the empirical results into a dynamic model of utilization adjustment in response to power outages and estimate structural cost parameters. This allows me to estimate the magnitude of power outages. I show that the impact of power outages is minimal for the LSM firms in my sample over the two year time span. During periods of frequent outages, costs for most firms increase by less than 3%. Based on the results from my limited sample, LSM firms in the chemical and textile industries have higher increases in cost than firms, of comparable size, in other industries. Although the sample is small, this finding is consistent with a recent survey in Pakistan(Siddiqui et al., 2011).

My results suggest that large firms can be successful in minimizing the detrimental effects of power outages. This is relevant to the 'missing middle' puzzle which notes that developing countries have far less medium sized firms than their more developed counterparts. Among the reasons that have been proposed to explain the puzzle are transaction costs, regulation, poor institutionalized support for small and mid sized firms and bias against small firms in industrial policy. These proposed explanations do not take into account aspects of the business environment, which are specific to developing countries, like frequent disruptions in electricity supply. Large firms in these environments are able to minimize the effects of these shocks and so small/medium sized firms may be more negatively impacted without the existence of any explicit bias.

Chapter 2

The Impact of Power Outages on Manufacturing Firm Exit

2.1 Introduction

The decision of a manufacturing firm to exit the market has profound implications on a variety of important economic indicators, from employment to productivity growth. Although firm exits can increase unemployment, the reallocation of resources from less productive to more productive uses (commonly referred to as "creative destruction") is a mechanism that is broadly thought to be beneficial (Bartelsman et al., 2004). This process is supported by empirical work which has found the measured productivity of exiting firms to be lower than that of incumbents (Roberts and Tybout, 1996).

However, during episodes of turbulence in a country's economic environment, firms which are forced to exit may not correspond to the least efficient firms in the market. For example, when the Argentine exchange rate regime collapsed in the 1980s, firms with dollar-denominated debt experienced exits and so, during that period, exit patterns were largely unrelated to productive efficiency (Swanson and Tybout, 1988). When these periods do occur, the impact of firm exits can be detrimental to an economy. In this paper, I study the impact of massive power outages on firm exits in Pakistan from 2009-2012 and demonstrate that power disruption *differentially* impacted small firm exit probabilities.

Early work on entry/exit analyzed the empirical relationship between turnover and firm characteristics. Dunne et al. (1989) find that plant failure rates decline with size and age in their study of the U.S. manufacturing sector in the 1967-1977 period. This inverse relationship between exit rates and size/age has been confirmed in other settings (Alvarez and Gorg, 2009; Bernard and Sjoholm, 2003). Research has also documented that plants owned by a multiplant firm are less likely to exit, though this relationship is due to the fact that these plants are on average "larger, older, more productive and more likely to export, employ more capital and more skilled workers, and operate in industries with lower shutdown probabilities" (Bernard and Jensen, 2007).

In addition, there has been considerable work studying the relationship between exit and firm characteristics in the developing world. Shiferaw (2006) studies exit in Ethiopia and,

Table 2.1: Percentage of firms reporting a business environment element to be the top obstacle

Economy	Financial Access	Corruption	Electricity	Pol Instability
East Asia & Pacific	16.4	6.3	10.2	8.6
Eastern Europe/C. Asia	15.3	7.6	7.6	10.0
High-Income OECD	11.1	5.1	3.9	11.9
Latin America	15.0	6.6	8.8	6.4
Middle East	7.7	9.5	13.2	17.3
South Asia	14.3	5.8	28.7	13.4
Sub-Saharan Africa	20.2	6.3	21.4	6.4

2002-2011 Enterprise Survey Data

among his many findings, demonstrates that entry and exit are predominantly observed among small firms. In Chile, Liu (1993) shows that exiting firms are less efficient than their counterparts - supporting the theory that firm death reallocates resources from less efficient to more efficient firms. However, Tybout (2000) points out that entrants in Chile and Colombia are typically less productive than existing firms on average and so "inefficient plants are being replaced with plants that are only slightly more efficient, and neither group is a source of much production."

The considerable emphasis that researchers place on small firms, especially in the developing world, is due to the fact that micro and small enterprises account for the bulk of employment (World Bank Publications, 2012). In addition, small firm survival is important for competition within the market i.e. without new entrants and potential competitors, large incumbent firms have an incentive to increase markup, decrease development of new products, etc. Therefore, although the turnover of small firms is unlikely to cause large changes in short-term production, the impact on the employment of low skilled labor and on market efficiency is likely to be significant.

One especially detrimental and ubiquitous challenge to firms in the developing world is power disruption. Striking evidence of the impact that energy disruptions have can be found in the World Bank's *Enterprise Survey*. In this survey, firm owners and managers are asked to identify a business environment element from a comprehensive list that "represents the biggest obstacle faced by this establishment." This list includes elements that have been identified in the economic development literature as having a first order influence on firms: political instability, corruption and financial access. However, business owners and managers in South Asia and Sub-Saharan Africa overwhelmingly choose electricity as the biggest obstacle that they face (Table 2.1). In the Middle East, electricity is cited as 'the biggest obstacle' more often than corruption or financial access.

Further evidence of the prevalence of power outages can be found in the EBRD-World Bank Business Environment and Enterprise Performance Survey (BEEPS). BEEPS is a joint initiative of the European Bank for Reconstruction and Development and the World Bank. The survey covers a broad range of issues about the business environment of firms, similar to the Enterprise Survey, and covers virtually all of the countries of Central and Eastern Europe as well as Turkey. In the recent 2008 round, over a third of the countries in the sample consider electricity as among the top 3 most severe problems that firms face (The World Bank Group, 2010). In addition, 90% of respondents in Albania and 57% of respondents in Turkey reported facing outages in the past year. The issue of power disruption becomes even more relevant as projected increases in energy demand come largely from the developing world (Energy Information Administration, 2011). Despite its clear importance, the effect of unreliable electricity supply on firm exit is an under-researched topic in economics.

In an environment of uncertain electricity supply, firms do adjust in order to minimize the detrimental impacts on cost and production. Many firms purchase diesel generators in order to keep production steady during a blackout. Steinbuks and Foster (2010) use annual data from the Enterprise Survey Database and study the prevalence of self generation in Africa. They find that firm size is an important determinant of owning a generator, with the probability of ownership doubling in large firms relative to small ones. However, while acquiring generation capacity is a popular response that firms make, it is certainly not the only one. Firms can also choose to vary capacity utilization by utilizing capital more intensely as well as having labor work overtime, work additional shifts or change shift timings (Ghaus-Pasha, 2009). The intuition behind these adjustments is clear. A firm can deliberately increase utilization while connected to the electricity grid in order to minimize the cost increases that are associated with using generators during a blackout. Increasing utilization does come with higher costs for machinery repair, maintenance, etc. The ability of small firms to adjust to outages is limited because these firms find it infeasible to purchase an independent generator due to a lack of financing options. Without independent generation, forced factory shut downs can lead to sizable cost increases caused by spoilage, machinery breakdown, labor costs, etc. Lee et al. (1996) note that since 'small firms cannot afford their own generators and boreholes and other facilities, the burdens of inadequate public infrastructure services are especially severe for the small firms which start and grow in those cities.'

Estimating the impact of power outages on firm exit is challenging because of data limitations and scope. Precise power outage data is difficult to obtain and so researchers often assume an average level of power outages per year, create a proxy based on power generation data or rely on survey responses. Furthermore, researchers often rely on official annual country level exit data in order to determine the impact of covariates on firm exit. This methodology lacks the precision of testing relationships at a high frequency. In this paper, I obtain proprietary data on the monthly incidence of unscheduled power outages as well as monthly electricity billing data. Using billing data, I directly observe the month in which a firm exits the market (i.e. when electricity consumption drops to less than 2000 kilowatt hours or when electricity consumption drops by more than 90%) and, because I observe firm connections to the electricity grid in Karachi, I am able to estimate the impact of power disruption on firms in the formal and informal sector. Merging these sources of data, I am able to exploit monthly variation in both power outages and firm exit.

Before summarizing my results, I graph the time series of monthly power outages (measured in 100 hour increments) and the fraction of exited firms by size in figure 2.1. Based on the upper plot of electricity outages, Karachi suffered from moderate outages in the last quarter of 2010 and suffered from high numbers of outages (over 100 hours of outages) in the third and fourth quarters of 2011 as well as in the first quarter of 2012. The lower plot represents the number of active clients determined to have exited the market divided by the total number of active clients for each size category. Exited firms are defined as the number of active clients which consume less than 2000 kWh in a month or which decrease electricity consumption by more than 90%. Small scale is defined as firms in the 30th percentile or below in the electricity consumption distribution, medium scale is defined as firms which consume electricity above the 30th percentile and below the 70th percentile, large scale firms are firms which consume electricity above the 70th percentile. When new clients establish a connection to the electricity grid, a new client account number is generated and the client is included in the total number of clients. In many cases, clients exit and return to the market in a subsequent period; when firms are categorized as exited for 4 successive periods, they are considered inactive clients and are dropped from the set of active clients.

The graphs taken together suggest two relationships. First, outages and firm exits do seem to be related to one another, with exits increasing significantly in the third and fourth quarters of 2011 as the number outages becomes high. Second, the firms which consume relatively low amounts of electricity seem to be more sensitive to outages than firms which consume higher amounts of electricity. I empirically test these claims using a variety of controls and show that, in fact, small scale firms are more sensitive to outages. I estimate that the exit probability of small scale firms increases by over 6% for each hundred hours of outages in a month. Because I estimate a short term impact and do not incorporate additional impacts such as potential firms choosing not to enter the market because of electricity shortages, I consider this estimate to be a lower bound.

My results propose and analyze a concrete mechanism through which power disruption affects firms and so it furthers the existing literature on the consequences of power disruption. In addition, my analysis contributes to the emerging, micro-based analysis of firm exit by using high frequency exit data in the context of a developing country. Finally, the broad result that medium and large scale firm exit probabilities are only moderately affected by electricity disruptions while small scale firm exit probabilities are more significantly affected helps to inform the discussion of the 'missing middle' (Tyler and Oppenheim, 1986; Tybout, 2000). Researchers have proposed several possibilities why the firm size distribution in developing countries is often comprised of a large number of small firms, relatively few medium sized firms and a small number of large firms. Among these reasons include policies that explicitly favor large firms such as investment incentives and tax breaks as well as de facto advantages like access to credit due to large firms' relatively low risk. In this paper, I note that my results are consistent with an alternative explanation for the missing middle in which small firms are *disproportionately* impacted by systemic shocks. An environment in which small firms have a higher probability of exit, for example during periods of power disruption, would prevent these firms from growing to become medium-sized firms; and this would, in turn, lead to a smaller mass of medium sized firms, relative to developed countries.

This paper is similar to recent work that attempts to analyze the determinants of firm exit (Bernard and Jensen, 2007). The authors use annual plant level data in the U.S. to study

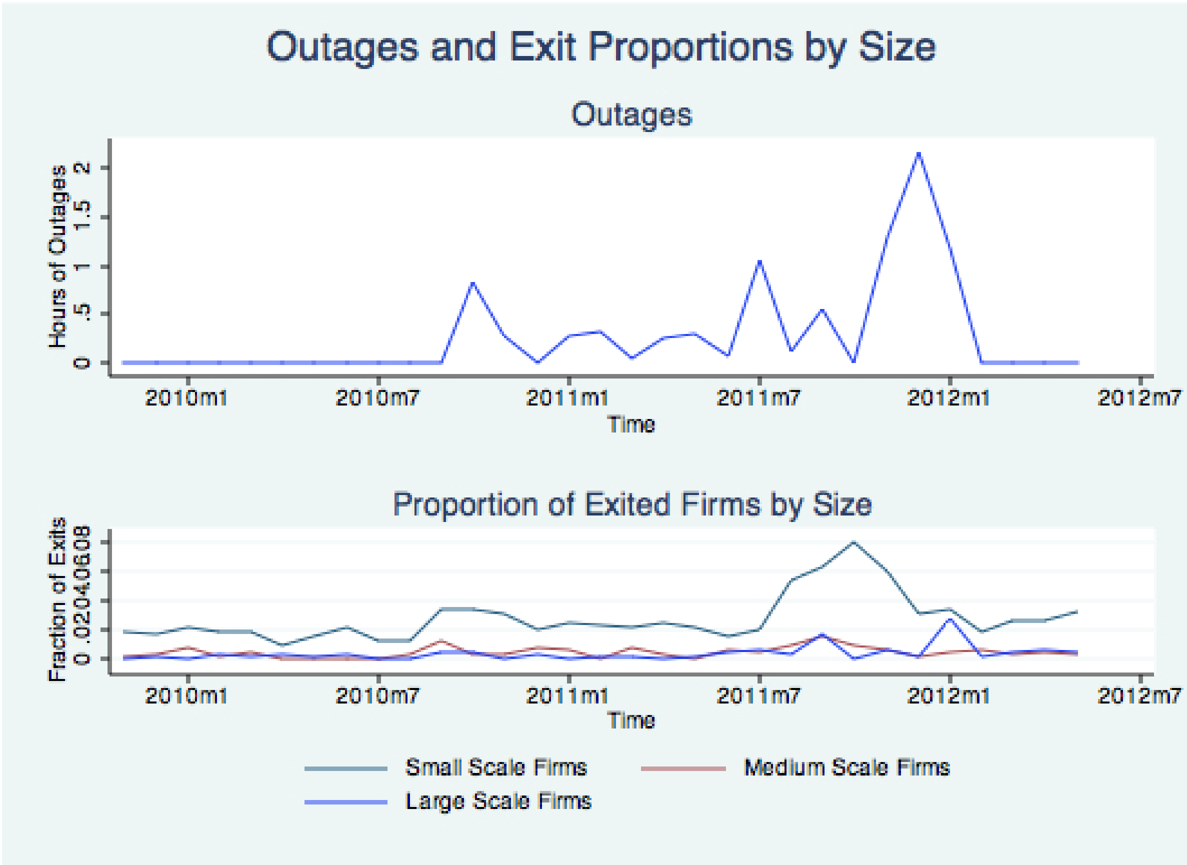

Figure 2.1: **Note**The top plot follows the number of hours of power outages for industrial clients in Karachi from November 2009 - March 2012. The lower plot represents the number of active clients determined to have exited the market divided by the total number of active clients for each size category. Exited firms are defined as the number of active clients which consume less than 2000 kWh in a month or which decrease electricity consumption by more than 90%. Small scale is defined as firms in the 30th percentile or below in the electricity consumption distribution, medium scale is defined as firms which consume electricity above the 30th percentile and below the 70th percentile, large scale firms are firms which consume electricity above the 70th percentile. When new clients establish a connection to the electricity grid, a new client account number is generated and the client is included in the total number of clients. In many cases, clients exit and return to the market in a subsequent period; when firms are categorized as exited for 4 successive periods, they are considered inactive clients and are dropped from the set of active clients.

the implications of being part of a multiplant firm on a plant's exit probability. They find that plants belonging to multi-plant firms and those owned by U.S. multinationals are less likely to exit, however this decrease in exit probabilities is due to the characteristics of the plants rather than the inherent nature of the firms. When the authors control for plant and industry attributes, they find that plants owned by multiunit firms and U.S. multinationals are more likely to close. There are two crucial differences between this analysis and my paper. First, I use exit and outage data at a much higher frequency and so this allows me better identification of short term impact of power outages. Second, I study exit probabilities in the context of a developing country in order to understand the relationship between energy disruption and exit.

This paper is also broadly similar to recent work that analyzes the costs of blackouts in

China (Fisher-Vanden et al., 2012). The authors create an annual measurement of electricity scarcity, which they argue is a proxy for power outages, and then use annual firm level data to estimate translog cost and value share equations to characterize the cost of blackouts which affected China in the early 2000s. They find that the overall effect of blackouts was to increase production costs by 2%-20%. There are two differences between this analysis and my paper. First, I make an explicit distinction between small, medium and large scale firms in order to estimate more precise effects of power disruption for each size of firm. Second, I consider the impact of outages on exit probabilities and not firm cost.

The remainder of this paper is organized as follows. In section 2, I provide an overview of the history of power outages in Karachi. I describe my data in section 3. In section 4, I discuss my empirical strategy and then run regressions to establish the relationship between power disruption and firm exit probabilities. Section 5 concludes.

2.2 Background

Power Outages in Karachi

Electricity demand grew gradually from the time of Pakistan's independence in 1947 due to urbanization, industrialization and rural electrification. By the 1990s, demand had increased beyond generation capacity to the point that compulsory power outages were necessary (Siddiqui et al., 2011). In 1993, the government established an Energy Task Force that recommended privatizing the energy sector and providing incentives to attract foreign investment. These recommendations led to the establishing of independent power producers (IPPs), which now account for approximately 25 percent of generation capacity, as well as to the privatization of KESC, Karachi's electricity provider, in 2005 (Shoaib, 2012).

Unfortunately, the alleviation of energy shortages was short-lived due to the unprecedented growth in the demand for electricity (over 7 percent per year) during past decade (2000-2010) without a corresponding increase in generation capacity (Asif, 2011). According to Karachi Electricity Supply Company (KESC) data, firms in Karachi today can face over 100 hours per month without power from the grid. The Enterprise Survey conducted in Pakistan in 2007 shows how dramatically business owners and managers across industries feel constrained by these disruptions (Table 2.2). In addition, local newspapers often quote leading industrialists as saying that electricity outages are severely detrimental to the manufacturing sector (Dawn Newspaper January, 2012; Daily Times Newspaper April, 2012). The Ministry of Finance is unequivocal in its assessment, "During 2011-2012, energy outages in Pakistan continued to be *the dominant constraint* in its growth" (Shoaib, 2012).

The electricity disruptions in Pakistan today have several causes. Generation capacity fluctuates seasonally with hydro generation dropping during the December-January period due to irrigation requirements on the dams and rainfall patterns. In addition, peak demand is influenced by seasonal fluctuations in residential demand such as air conditioning in the summer.[1] Periodic decreases in the supply of natural gas for KESC's generation has also

[1] Electricity consumption is divided between household (46 percent), industrial (29 percent), agricultural

Table 2.2: Percentage of firms reporting a business environment element to be the top obstacle in Pakistan

Sector	Financial Access	Corruption	Electricity	Pol Instability	N
Food	1.1	10.1	64.7	1.8	125
Textiles	0.4	3.2	87.7	1.0	192
Chemicals	0.0	8.3	68.2	0.0	20
Machinery	7.3	10.9	71.2	0.2	47
Other Man.	5.8	18.4	57.7	0.8	274

2007 Enterprise Survey Data

resulted in lower generation capacity and blackouts (Express Tribune Newspaper, 2009). Finally, fluctuations in the price of fuel and in the amount of electricity supplied by independent power producers (IPPs) can cause shortfalls. In December 2008, KESC changed its policy to exempt the industrial zones from scheduled power outages and so, with a few exceptions, *power outages in Karachi's industrial zones are unscheduled*.

When outages occur, firms make several adjustments to operations. Popular adjustments include acquiring self-generation capacity and more intensive utilization of capacity (both machinery and work shifts) (Ghaus-Pasha, 2009). Both cause an increase the in cost of production. Self-generation capacity relies on the use of diesel generators and so manufacturing costs increase due to the difference in price between diesel and electricity from the grid, transportation costs, etc.; Pakistani researchers estimate the cost of diesel to be approximately two and a half times higher (Sheikh, 2008). More intensive capacity utilization is associated with overtime as well as higher repair and maintenance costs (Pasha et al., 1989).

A more dramatic measure that some firms take is to acquire captive power. In Karachi, this refers to firms which have natural gas delivered to power natural gas generators and use power from KESC intermittently to complement their own generation or when there are disruptions in the natural gas supply. In doing so, these firms are (to varying degrees) insulated from disruptions in the electricity supply.

Many of the adjustments discussed above are more difficult for small scale firms. Purchasing and maintaining independent generators can be prohibitively costly, particularly in developing countries, because of significant financial constraints (Beck et al., 2009). Captive power is also prohibitively costly because firms require natural gas generators. In addition, managing capacity utilization requires that a firm has excess capacity; in discussions with firm managers in Karachi, this is less likely for small firms as they run continuously. As alluded to in the introduction, small scale firms provide a large share of employment, while large scale manufacturing dominates manufacturing output (World Bank, 2002); and so understanding the impact of power disruption on the exit probabilities of the full firm size distribution can be useful in understanding how energy shortages impact the broader economy.

(11 percent), commercial (7 percent), bulk supplies (6 percent) and street lights (1 percent). (Khan and Qayyum, 2009)

2.3 Data

An innovation of this paper is the use of electricity billing data to determine the month that firms, in both the formal and informal sector, exit the market. Electricity billing data come from KESC, the sole provider of electricity in Karachi. This data includes monthly electricity usage in kilowatt hours for all clients in the two main industrial zones of Karachi (Korangi and SITE) from September 2009 to March 2012. For empirical work, this is an extremely useful source of accurate, high-frequency, firm-level data.

KESC also provides a detailed list of power outages at the hourly level from September 2009 to March 2012. This data is aggregated at the monthly level for regression analysis. Since December 2008, KESC policy has been to exempt industrial zones from scheduled outages.[2] Therefore, the vast majority of electricity disruptions are unscheduled. The maximum number of hours without power is 216 hours, which occurred in December 2011, while some months in early 2010 suffered from no outages. In each month, the same number of hours of outages occur in all industrial zones.

The monthly spot price of cotton in Karachi was collected from the leading financial business daily of Pakistan, the Business Recorder.

2.3.1 Construction of Size and Exit Variables

I construct a simple measure of firm size using the distribution of electricity consumption. The implied assumption is that electricity consumption is a proxy for firm size. First, I drop all firms with average electricity consumption below 5000 kilowatt hours in order to remove commercial and residential clients from the data.[3] This leads to a sample of 673 industrial clients.

Specifically, I define small scale manufacturing as firms below the 30th percentile of monthly electricity consumption. Similarly, I define medium scale manufacturing as firms which consume electricity between the 30th and 70th percentile of monthly electricity consumption, and large scale manufacturing as firms which consume electricity greater than the 70th percentile of monthly electricity consumption.

A main contribution of this paper is the use of electricity consumption data to determine the precise timing of firm exit. For each firm, if monthly electricity consumption drops below 1000 kilowatt hours or if electricity consumption drops by 90% or more, then I define that as an exit. My results are not dependent on the 1000 kilowatt hour cutoff.

[2] In the last quarter of 2011, scheduled outages did occur due to natural gas shortages.

[3] Although the industrial zones contain mainly the manufacturing plants, there do exist commercial and residential clients. Therefore, I drop any client that consumes less than an average of 5000 kilowatt hours. My results are robust to different threshold choices.

Table 2.3: Effect of Outages on Likelihood of Firm Exit

	(1) Probit $Exit_{i,t+1}$	(2) Probit $Exit_{i,t+1}$	(3) OLS $Exit_{i,t+1}$	(4) OLS $Exit_{i,t+1}$
$Outage_t \times SSM_i$	0.458^{***}	1.519^{*}	0.052^{***}	0.065^{***}
	(0.04)	(0.91)	(0.01)	(0.01)
$Outage_t \times MSM_i$	-0.388^{***}	0.667	-0.014^{***}	0.013
	(0.10)	(0.92)	(0.00)	(0.01)
$Outage_t \times LSM_i$	-0.005	1.114	0.000	0.039^{***}
	(0.07)	(0.91)	(0.01)	(0.01)
Industry FE		Y		
Firm FE				Y
Month FE		Y		Y
R^2			0.010	0.131
N	21503	21503	21503	21503

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors clustered at firm level

2.4 Empirical Results

Testing for the determinants of firm exit often involve a probit or logit estimation strategy. Unfortunately, the incidental parameters problem arises when incorporating firm fixed effects using maximum likelihood on data with the number of time periods held constant and the number of firms large[4] The inconsistency of maximum likelihood estimators presents a problem because the inclusion of firm fixed effects would significantly help to identify the impact of power outages on firm exit. In order to include firm fixed-effects in the empirical model, I construct a linear model with the following specification:

$$Exit_{i,t+1} = \beta_0 + \beta_1 Outage_t \times SSM_i + \beta_2 Outage_t \times MSM_i + \beta_3 Outage_t \times LSM_i + \nu_t + \phi_i + \epsilon_{it}$$

Here, $Exit_{i,t+1}$ refers to the measure of firm exit described in the previous section for firm i and month $t+1$. Month fixed effects in this regression, ν_t, control for systematic differences in exit each month that do not depend on the number of hours without power; these can include the effects of oil price changes, city-wide strikes and violence. Firm fixed effects, phi_i, control for systematic differences in exit likelihood across firms for all periods; these differences can include whether a firm is foreign owned, the firm's industry, etc.

The coefficients of interest are β_1, β_2 and β_3. These coefficients represent the impact of power outages on the likelihood of firm exit for small, medium and large scale manufacturing firms. The results of this estimation, as well as the estimation of probit models, are reported in Table 2.3.

In the first column, I estimate a probit model with only the three interaction terms, representing the impact of outages on firms of differing size. I find that the exit likelihood of SSM firms is significantly increased in the months following outages. MSM firms seem to

[4] Under these conditions, the maximum likelihood estimator can be inconsistent.

have the opposite effect but this effect is insignificant with the inclusion of time and industry fixed effects in the second column. Although the significance of the impact of outages on SSM decreases with the inclusion of time and industry fixed effects, the effect remains significant at the 10% level.[5] In the third column, I run a linear model similar to (1) without the fixed effects as controls. Again, I find that the exit probability of SSM firms significantly increases when power outages occur and this result remains when I include month and firm fixed effects in the fourth column. I also find that the exit probability of LSM firms significantly increases when including the controls, though the magnitude of this increase is lower than than the increase for SSM firms. These results are consistent with small scale manufacturing firms bearing the brunt of the impact of power outages.

2.5 Robustness

There are several potential concerns with the main empirical results. First, my results may be driven by the way that I define small scale, medium scale and large scale manufacturing firms. To address this concern, I interact outages with a measure of the size of a firm - natural log of the consumption of electricity in table 2.4. To account for nonlinear effects, I also include a squared interaction term. Consistent with my results, in both the probit and OLS specification of columns (1) and (2), I find that the coefficient on the interaction is negative and significant or that smaller firms are impacted more by outages. I do find that there are nonlinear effects, specifically that the coefficient on the squared term is positive and significant. This suggests that large scale manufacturing is also impacted by outages, although the impact on large scale manufacturing is lower than the impact on small scale manufacturing in every specification. Coefficients on the lagged interaction and squared term have the same sign with smaller magnitudes.

Second, my results may be driven by firms in a particular industry. In columns (3) and (4), I drop firms from the textile and non-metallic mineral products industries - the two industries with the most firms in my sample. My main results continue to hold. Second, I include a lagged dependent variable in my specification and, again, find that my results continue to to hold. Finally, it is possible that market forces may be determinants of firm exit which are being omitted. Because of data limitations, I do not directly observe the prices of all raw materials for the industries - however I do directly observe the spot price of cotton during the sample period. Therefore, I restrict my sample to only textile firms and include the spot price of cotton and the lagged spot price of cotton. The impact of the price of cotton is minimal, while the impact of outages on small scale manufacturing continues to be significant and the point estimate continues to be higher than for medium and large scale manufacturing.

[5] I include industry fixed effects and not firm fixed effects in the non linear specifications because of the incidental parameters problem described above.

Table 2.4: Effect of Outages on Likelihood of Firm Exit - Robustness

	(1) Probit $Exit_{i,t+1}$	(2) OLS $Exit_{i,t+1}$	(3) OLS $Exit_{i,t+1}$	(4) OLS $Exit_{i,t+1}$	(5) OLS $Exit_{i,t+1}$	(6) OLS $Exit_{i,t+1}$
$Outage_t \times size_{i,t}$	-1.067***	-0.104***				
	(0.10)	(0.01)				
$(Outage_t \times size_{i,t})^2$	0.027***	0.003***				
	(0.00)	(0.00)				
$Outage_{t-1} \times size_{i,t-1}$	-0.392***	-0.027***				
	(0.07)	(0.01)				
$(Outage_{t-1} \times size_{i,t-1})^2$	0.010***	0.001***				
	(0.00)	(0.00)				
$Outage_t \times SSM_i$			0.09***	0.06***	0.04***	0.04***
			(0.02)	(0.01)	(0.01)	(0.01)
$Outage_t \times MSM_i$			0.02	0.01	0.02**	0.00
			(0.02)	(0.01)	(0.01)	(0.01)
$Outage_t \times LSM_i$			0.05***	0.05***	0.03***	0.02
			(0.02)	(0.01)	(0.01)	(0.02)
$Exit_t$					0.39***	
			(0.02)			
$Cotton_t$						0.00***
						(0.00)
$Cotton_{t-1}$						-0.00
						(0.00)
Industry FE	Y					
Firm FE		Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
R^2		0.15	0.11	0.14	0.26	0.16
N	19782	20429	14179	15165	21503	7053

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors clustered at firm level

2.6 Conclusion

Electricity outages are ubiquitous in the developing world and there is little direct, high frequency analysis of exactly how these outages impact manufacturing firms. This paper is an attempt to address this open question by focusing on firm death over the full firm size distribution in Karachi, a city with high numbers of power outages during the period that I analyze.

By using a proprietary dataset from the only supplier of grid electricity in Karachi, I identify the month of a firm exit by observing when the consumption of electricity falls. In addition, I use precise outage data provided by only electricity provider in the city to analyze how electricity disruption impacts firm death. The high frequency nature of this data allows me to use monthly variation in the frequency of power outages to precisely determine whether outages do lead to firm death.

Unsurprisingly, I find that power outages do impact the likelihood of firm exit in Karachi. I find some evidence that the exit probability of LSM firms increases as a result of power outages, though this increase is far less than the increase in exit probability for SSM firms. In months with over 300 hours without power, the likelihood of firm death increases by approximately 20%. This result is robust to the inclusion of firm and time controls as well as market controls.

While much of the literature on the firm impact of power disruption analyzes a mean effect across the full firm size distribution, my results provide strong evidence of a disproportionate impact on small scale manufacturing. These firms often do not have independent generation capability and so the costs of energy disruption are significantly higher due to spoilage, machinery breakdown, etc. Lee et al. (1996). By targeting alleviation strategies to benefit the smallest firms, public policy programs are far more likely to address the short term costs of power outages.

Chapter 3

Religious Holidays and the Incidence of Religious Violence in India

3.1 Introduction

Violence between the Hindu and Muslim communities in South Asia is an enduring phenomenon. One of the earliest accounts occurs in Ahmedabad in 1730 when a Hindu man lit a fire for the Hindu holiday Holi against the wishes of his Muslim neighbor (Saxena, 1984). Post-independence India has not been free from the same communal tensions that have plagued the region for centuries. While the Bombay riots of 1992-1993 and the Gujarat riots of 2002 were certainly the most publicized, communal violence occurs constantly - political scientist Paul Brass explains, "hardly a month passes in India in which a Hindu-Muslim riot does not occur that is large enough to be noted in the press" (Brass, 2003).

One of the few estimates of damage done to a state economy by Hindu-Muslim rioting was performed by the research group Tata services which estimates a loss of 9,000 crore ($3.6 billion) divided between loss of gross value of output, loss of exports, loss of tax revenue and loss of property caused by the Bombay riots in 1992-1993 (Engineer, 2004). The Indian government also periodically establishes commissions to investigate the causes and consequences of riots. For instance, in 1967 the Indian state of Bihar debated whether Urdu should be recognized as an official language. Tensions flared and the commission that investigated the subsequent riots estimated the total damage to be Rs. 1,420,000. This damage was distributed across residential housing, shops and businesses, places of worship and one school. Loans which amounted to Rs. 1 lakh were distributed to residents who were affected by the violence including widows who were given 'maintenance grants.' The final cost in the form of loans, property damage and other expenditures was about 2 million Rs. (Dayal, 1969). In addition to the economic costs, large scale rioting also displaces many thousands and leads to significant human suffering.

Various authors have suggested possible causes of communal violence in India. Political scientist Paul Brass emphasizes the role of elite manipulation in institutionalized riot systems which attempt to foment conflict in order to maintain electoral strength (Brass, 2003). In a similar vein, political scientist Steve Wilkinson focuses on electoral competition and finds, among other things, that an upcoming national or state election increases the possibility of violence as does the closeness of the previous Vidhan Sabha constituency race in the state of Uttar Pradesh (Wilkinson, 2004). This result runs contrary to the political economics literature which suggests that close elections create incentives for political agents to placate constituents in order gain a larger vote share.

On the other hand, both Jha and Varshney focus on civic engagement and the institutional mechanisms that constrain religious violence. Jha suggests that in areas in which medieval Hindus and Muslims could provide "complementary, non-replicable services and a mechanism to share the gains from trade" a legacy of religious tolerance ensued. Even today, he argues that this legacy helps to constrain violence (Jha, 2007). Varshney focuses on civic engagement and argues that associational forms of civic engagement like trade unions and professional associations are able to control outbreaks of ethnic violence (Varshney, 2002).

Sergenti and Anjali focus on the links between economic conditions and violence (Sergenti and Thomas, 2005). They follow the methodology of Miguel et. al. in using rain as an instrument for economic growth and ask if negative growth shocks serve as triggers for communal violence (Miguel and Sergenti, 2004). This yearly level study finds that growth shocks do affect the incidence of violence.

Other authors suggest a linkage between religious holidays and communal violence. Norman Brown lists different triggering events in nineteenth-century India and among them he notes "the clash of crowds when a Hindu and a Muslim festival coincided" (Brown, 1963). Stanley Tambiah explains "[religious] processions predictably trigger violence between polarized communities, especially when they traverse the other's territory ... [thus] festival calendars can at sensitive times actually channel and direct the shape, expression, timing and spatial location of ethnic violence." In his book criticizing police inaction during riots, Vibhuti Rai explains how religious holidays can lead to violence, "There are many spots in a town or city where crowds collect either at different times of the day or night In the Indian context, there are many significant examples of how an existing crowd could be used for communal mobilization " (Rai, 1999). Religious groups often have processions to celebrate holidays and so they provide the potential for violence - although not all processions end in violence. Asghar Ali Engineer points out that religious processions alone are not the cause of communal riots, they merely provide an occasion for violence to be "sparked" (Engineer, 1989). The route of a procession can instigate violence if, for example, a Hindu procession passes by a mosque. In addition there are instances of private celebrations causing communal tension when a Muslim sacrifices a cow or a Hindu sets a fire for Holi.

The period surrounding a religious holiday can be just as tense as the day itself because of preparations. In the *Report of the Commission of Inquiry on Communal Disturbances 1967*, authors describe the history of communal tension in Bihar, "Ranchi-Hatia had shown signs of communal tension from time to time, especially on the question of taking out of religious processions . . . In April, 1964 serious tension developed at Ranchi on the eve of the Ram Navamy festival when the extremist section of the Mahavir Mandal Committee refused to abide by the demands of saner sections regarding the control of Mahaviri Jhanda processions..." (Dayal, 1969)

Stanley Tambiah also suggests that political parties can use these periods of increased tension for political gain by precipitating violence: "timing rath yatras [political marches] to take place at the time of festivals such as Dussehra ... not only ensure[s] the spectator-presence ... but also lend to the processions, which embody a large potential for violent acts ... [these] acts and events form a repertoire of collective violence linking up with and drawing from the collective calendrical festivities and celebrations of public culture" (Tambiah, 1996). Tambiah's argument that political agents instrumentally use religious holidays to further their electoral goals is not the alone. Amalendu De writes, "branches of RSS began to celebrate the Ram-Navami festival with much enthusiasm" and in doing so used the holiday for political gain (De, 1994). Brass writes "Riots accompany political mobilizations around religious symbols and contribute to the strengthening of the movements, which in turn solidify communal solidarity in subsequent elections ... riots persist because they are functionally useful to a wide array of individuals, groups, parties and the state authorities" (Brass, 2003).

Here, I address two separate but related questions. First, I ask whether religious holidays do indeed affect the incidence of communal violence and whether the interaction of Hindu and Muslim holidays in the same month has a further effect on violence. I show that both religious holidays and the interaction of Hindu and Muslim holidays positively affect the incidence of violence. I also show that the states for which the interaction effect is large and significant are also the states that have more overall violence. This is consistent with the theory that violence is triggered in some states because of its functional usefulness. Second, I consider the usefulness of violence by determining the electoral effects of violence on vote share. I find that violence before an election is associated with electoral gains for Congress and losses for the rival Janata Parties in certain states in the 1980s.

3.2 Data and Methodology

Data on the instances of communal violence comes from the Varshney-Wilkinson dataset. This dataset includes information on the location, duration and date of riots reported in the major Indian newspaper *The Times of India, Bombay edition* between 1960 and 1990. As indicated in the supporting documentation, it was collected from $1993 - 1996$ by political scientists Ashutosh Varshney and Steven Wilkinson and is available from the Inter-University Consortium for Political and Social Research (ICPSR) database.

Election data as well as some socioeconomic data is taken from the Besley-Burgess dataset which is generously made available by the authors.[1] This data is at the yearly level and so I download data from the Election Commission India website to determine the precise date of an election.[2] The Besley-Burgess data provides yearly observations on state domestic product for all of the states of India in the study as well as observations for rainfall, voter turnout and vote share for Vidhan Sabha (state legislature) elections. For information on the proportions of different religious groups by state and on gender literacy, I turn to the

[1]http://sticerd.lse.ac.uk/eopp/research/indian.asp

[2]http://www.eci.gov.in/StatisticalReports/ElectionStatistics.asp

Table 3.1: List of Official Holidays of the Indian Government

Holiday	Type of Holiday	Holiday	Type of Holiday
Republic Day	National	Dussehra	Hindu
Independence Day	National	Diwali	Hindu
Mahatma Gandhi's Birthday	National	Holi	Hindu
		Janamastami	Hindu
Buddha Purnima	Buddhist	Ram Navami	Hindu
		Mahashivratri	Hindu
Guru Nanak's Birthday	Sikh	Ganesh Chaturthi	Hindu
Mahavir Jayanthi	Jain	Makarasankaranti	Hindu
		Rath Yatra	Hindu
Christmas	Christian	Onam	Hindu
Good Friday	Christian	Pongal	Hindu
		Sri Panchami	Hindu
Eid ul Fitr	Muslim	Vishu	Hindu
Eid ul Zuha	Muslim	Vaisakhi	Hindu
Eid e Milad	Muslim	Bhag Bihu	Hindu
Muharram	Muslim		

government of India publication *The First Report on Religion Data* which has data from the various censuses (Various, 2001).

The Indian Meteorological Department issues a calendar each year which provides the dates of all major religious holidays and national holidays (Department, 1991). From these calendars I obtain the dates of compulsory and optional holidays observed by the government of India from 1960 - 1990; the list of official holidays and optional holidays was taken from *Holiday Policy & Hours of Work 2002*. The official holidays are divided between national holidays and religious holidays. Among the list of religious holidays are Hindu and Muslim holidays as well as Jain, Buddhist and Christian holidays. Table 1 lists the official holidays.

3.3 Empirical Analysis

Since the data on the number of incidents of communal violence is count data, I run OLS, IV-2SLS and Negative Binomial regressions. The first set of OLS regressions simply tests whether the set of official holidays and other covariates significantly affects the incidence of communal violence. Note that since the religious holiday data is at the daily level while the socioeconomic data is at the yearly level we can account for both types of variation whereas previous studies could only account for yearly level variation. For states s and days d the OLS regression takes the following form:

$$v_{s,d} = \beta_0 + \phi z_{s,d} + \gamma h_{s,d} + \alpha_s + \delta_d + \epsilon_{s,d}$$

where $v_{s,d}$ is the number of incidents of violence for state s in day d and α_s and δ_d are state and time fixed effects respectively (δ_d includes day, month and year fixed effects). The variable $z_{s,d}$ is a vector of socioeconomic variables including literacy rate by gender, proportions of each religious group by state and state domestic product. Since the literacy data and religious makeup of each state is measured during each census, the values only change every 10 years. The variable $h_{s,d}$ is a vector of official holidays which include national holidays like independence day as well as Hindu, Muslim, Jain and Buddhist holidays. The IV-2SLS specification simply uses the percent change in rainfall as an instrument for the percent change in state domestic product. The negative binomial regression includes the same covariates as the OLS regression but is obviously parameterized differently.[3]

The second set of regressions adds political variables like voter turnout, an indicator for the day of an election and a measure of competitiveness of the previous election. The competitiveness measure is created using the method of Besley and Burgess in which the absolute difference is taken "between the proportion of seats occupied by the Congress party (which has been the dominant party over the period) and the proportion occupied by its main competitor(s)" (Besley and Burgess, 2002). In addition to the political variables, I add the indicators $Hindu$ and $Muslim$ which take a value of 1 if a religious holiday occurs in a particular month and 0 otherwise as well as an interaction variable which takes a value of 1 if a Hindu and Muslim holiday occur on the same month and 0 otherwise to allow for the possibility of increased propensity for violence when religious holidays coincide. The IV-2SLS regression instruments for state domestic product and the negative binomial regression includes the same covariates as the OLS regression.

The third set of regressions interacts the Hindu $\times$ Muslim indicator with the various state indicators in order to allow for a differential effect for each state. The IV-2SLS regression and negative binomial regressions are run analogously to the earlier regressions.

Finally, the vote share regressions test whether violence in the month before an election (and other covariates) affect the electoral results of the Congress and Janata parties. [4] Because the values of the dependent variable are large (and so would not suffer from count data issues), I do not include a negative binomial specification. For state s and election e the OLS regression takes the following general form:

$$vs_{s,e} = \beta_0 + \rho * vs_{s,e-1} + \phi * z_{s,e} + \gamma * v\_short\_term_{s,e} + \lambda * v\_long\_term_{s,e} + \alpha_s + \delta_e + \epsilon_{s,e}$$

where $vs_{s,e}$ is the vote share for a particular grouping of parties (either Congress or Janata) in a Vidhan Sabha (state legislature) election, $vs_{s,e-1}$ is the vote share in the previous

[3] The negative binomial model assumes the conditional distribution of the dependent variable is $f(y|\lambda, u) = \frac{\Gamma(y+\alpha)}{\Gamma(\alpha)\Gamma(y+1)}\left(\frac{\alpha}{\lambda+\alpha}\right)^{\alpha}\left(\frac{\lambda}{\lambda+\alpha}\right)^{y}$ with the parameterization $\lambda = e^{x'\beta}$ and the estimator $\hat{\beta}$ is estimated via maximum likelihood.

[4] Besley and Burgess point out, "The main political threat over the period has come from the Janata grouping of parties..." I construct this grouping in the same way (Besley and Burgess, 2002).

election, $z_{s,e}$ is a vector of covariates, $v\_short\_term_{s,e}$ is the number of incidents of violence in the month before the election, $v\_long\_term_{s,e}$ is the number of incidents of violence between 2 months and 2 years before an election and finally α_s and δ_e represent state and year fixed effects.

3.4 Results

Table 2 presents the baseline results on the determinants of incidence of communal violence. Only the most significant religious holidays are included in the table for space considerations.[5] Column (2) contains the OLS specification with day, month, year and state controls and indicates that a higher percentage of Hindus or Muslims increases expected number of incidents of communal violence. The inclusion of the percentage of Christians, Buddhists and Jain citizens by state is a robustness check and understandably decreases the expected number of incidents. The IV-2SLS specification demonstrates that negative growth shocks do indeed affect the incidence of communal violence.

One potential argument against the inclusion of holidays is idea that holidays fall at the same time each year and so identifying the effect of the holiday would be difficult because it may be merely a proxy for some time effect. Although this is true for most holidays in America (for instance Christmas falls on the same day each year), religious holidays in India change their date each year. Hindu holidays do not follow the Gregorian calendar, instead they follow the Hindu Calendar while Muslim holidays follow a lunar cycle and so the date of any holiday regresses by about 10 days each year. Table 3 illustrates this point by tracking the date of the Hindu holiday Dussehra and the Muslim holiday Muharram. Additionally the day, month and year controls should capture the variation in rioting that is attributable to simple time effects.

As for the effect of religious holidays, the impact is more complicated. Three of the four Muslim holidays do seem to increase the expected number of incidents; however, while some Hindu holidays (Dussehra, Holi) seem to be associated with more violence there are other holidays (Vaisakhi, Diwali and Sri Panchami) that are associated with less violence. Understanding the differences between hindu holidays is important to interpret this result. Some Hindu holidays commemorate victories of Hindu gods, for example Dussehra is a holiday which signifies the victory of good over evil. On the other hand, some holidays are merely harvest festivals or have less antagonistic undertones - Sri Panchami is a spring festival in which followers celebrate the goddess of knowledge while Vaisakhi is a harvest festival. This empirical result suggests that although some holidays may indeed be associated with higher levels of violence, other holidays may serve to constrain violence.

So far, I have only considered the effect of socioeconomic variables and the specific day of a religious holiday. Based on previous discussion, it is plausible that political variables and periods in which Hindu and Muslim holidays occur near one another may affect the incidence

[5] The only holiday (official or religious) that is not a Hindu or Muslim holiday and is consistently significant is Good Friday. It is unclear why this is the case, but all other official holidays and non-Hindu or Muslim religious holidays are consistently insignificant.

Table 3.2: Effect of Religious Holidays and Socioeconomic Variables on Communal Violence

	OLS	OLS	IV-2SLS	Neg Bin	Neg Bin
Eid ul Fitr	0.0057	0.0052	0.0044	0.7410**	0.9612**
	(0.0041)	(0.0040)	(0.0042)	(0.3312)	(0.4426)
Muharram	0.0351***	0.0353***	0.0355***	2.1040***	2.2100***
	(0.0111)	(0.0111)	(0.0105)	(0.1779)	(0.2033)
Eid e Milad	0.0209**	0.0208**	0.0174**	1.4217***	1.3378***
	(0.0075)	(0.0075)	(0.0080)	(0.3177)	(0.3621)
Vaisakhi	-0.0059***	-0.0055**	-0.0062**	-17.6639***	-17.2464***
	(0.0017)	(0.0023)	(0.0025)	(0.4101)	(0.5601)
Dussehra	0.0347***	0.0324***	0.0370***	2.1885***	2.0703***
	(0.0100)	(0.0096)	(0.0103)	(0.2476)	(0.2919)
Diwali	-0.0045***	-0.0053***	-0.0059***	-19.1795***	-16.8696***
	(0.0012)	(0.0014)	(0.0015)	(0.3779)	(0.3889)
Sri Panchami	-0.0046***	-0.0035***	-0.0035***	-19.1942***	-16.5171***
	(0.0013)	(0.0010)	(0.0011)	(0.3858)	(0.3977)
Holi	0.0279	0.0274	0.0168***	1.7153***	1.5848***
	(0.0161)	(0.0168)	(0.0063)	(0.2482)	(0.4002)
Male Literacy	0.0004	-0.0002	-0.0001	0.0947*	0.0308
	(0.0002)	(0.0002)	(0.0003)	(0.0505)	(0.0500)
Female Literacy	-0.0000	-0.0001	0.0001	-0.0391	-0.0578**
	(0.0002)	(0.0003)	(0.0003)	(0.0505)	(0.0285)
Percent Hindu	0.0040	0.0892*	0.1274***	1.3416	8.9926*
	(0.0042)	(0.0446)	(0.0381)	(0.9875)	(5.3077)
Percent Muslim	0.0124**	0.0272	0.0320	3.0025**	4.4324
	(0.0051)	(0.0180)	(0.0231)	(1.2438)	(4.1589)
Percent Christian	-0.0679*	0.0828	0.1444	-16.7828*	5.5574
	(0.0387)	(0.0753)	(0.1310)	(9.8505)	(15.1671)
Percent Buddhist	0.0706	-1.4923*	-1.9424***	6.3017	-45.4722
	(0.0583)	(0.8208)	(0.6478)	(6.7646)	(67.1187)
Percent Jain	0.1941	-2.5790	-4.0222***	19.3736	-132.6053**
	(0.1771)	(1.6948)	(1.2933)	(31.3214)	(52.7915)
SDP Growth	-0.0055	-0.0076	0.0820**	-0.6485	-0.8206
	(0.0082)	(0.0100)	(0.0324)	(1.4092)	(1.5779)
SDP Growth$_{t-1}$	-0.0052	-0.0034	0.0295	-0.7966	0.0191
	(0.0072)	(0.0067)	(0.0283)	(1.0874)	(1.4825)
Day Month Year State Controls		Yes	Yes		Yes

Robust standard errors clustered at the state level are shown in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.3: Dates of Dussehra and Muharram

Dussehra	Muharram
9/30/1960	7/5/1960
10/19/1961	6/24/1961
10/8/1962	6/13/1962
9/28/1963	6/3/1963
10/15/1964	5/23/1964
⋮	⋮
9/19/1980	11/19/1980
9/8/1981	11/8/1981
9/27/1982	10/28/1982
10/16/1983	10/17/1983
10/4/1984	10/6/1984

of Hindu Muslim rioting. Table 4 takes into account these possible influences. Formally, the OLS specification is

$$v_{s,d} = \beta_0 + \phi z_{s,d} + \gamma h_{s,d} + \alpha_s + \delta_d + \omega p_{s,d} + \rho H_{s,d} \times M_{s,d} + \epsilon_{s,d}$$

where $p_{s,d}$ is a vector of political covariates, $H_{s,d}$ is a dummy variable that takes a value of 1 if a Hindu holiday falls in a particular month and 0 otherwise, $M_{s,d}$ is a dummy variable that takes a value of 1 if a Muslim holiday falls in a particular month and 0 otherwise and so $H_{s,d} \times M_{s,d}$ is an interaction. Since Hindu and Muslim holidays change their date each year, the interaction term $H_{s,d} \times M_{s,d}$ is not an indicator which simply captures time effects. Table 5 tracks this indicator.

Column (1) contains the OLS specification with day, month, year and state controls and indicates that voter turnout of most recent election has a negative effect on the incidence of rioting. On the other hand there is no significant effect of the month of an election or the month before an election on the expected number of riots. Note that religious holiday indicators are included in each regression and the magnitudes as well as significance do not change with the inclusion of the $Hindu \times Muslim$ variable.

The interaction term $Hindu \times Muslim$ is significant at the 5% level for both the OLS and Negative Binomial regression. In all cases the magnitude of the coefficient estimate is positive. These results suggest that months in which both a Muslim and Hindu holiday occur are likely to have more incidents of communal violence than months without both holidays. In fact the result would plausibly have been stronger if I could think of a defensible way to choose the Hindu holidays that seem most prone to violence, but as of now I have not been able to do this.

Table 3.4: Effect of Political Variables and Religious Holiday Interaction on Communal Violence

	OLS	2SLS-IV	NegBin
Voter Turnout	-0.0003**	-0.0003*	-0.0524***
	(0.0001)	(0.0001)	(0.0102)
Election Day	0.0055	-0.0038**	0.6486
	(0.0085)	(0.0018)	(0.7649)
Competitiveness Measure	-0.0027	-0.0032	-0.6647***
	(0.0016)	(0.0025)	(0.1782)
Month of Election	0.0003	-0.0004	0.1995
	(0.0016)	(0.0017)	(0.3531)
Month Before Election	-0.0021	-0.0026*	-0.5990
	(0.0015)	(0.0016)	(0.3801)
Hindu $\times$ Muslim	0.0013**	0.0016**	0.2558***
	(0.0006)	(0.0007)	(0.0955)
Religious Holiday Controls	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes
Day Month Year State Controls	Yes	Yes	Yes

Robust standard errors clustered at the state level are shown in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Months of $Hindu \times Muslim$

Year	January	February	March	April	May	June	July	August	September	October	November	December
1960			$\times$			$\times$			$\times$			
1961			$\times$					$\times$				
1962			$\times$					$\times$				
1963		$\times$				$\times$		$\times$				
1964		$\times$		$\times$			$\times$					
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	
1980	$\times$							$\times$			$\times$	
1981	$\times$							$\times$		$\times$		
1982	$\times$								$\times$	$\times$		
1983							$\times$		$\times$	$\times$		
1984									$\times$	$\times$		

One drawback of the regressions involving the interaction, $Hindu \times Muslim$, is that it assumes the effect is the same across states. At first this may seem plausible because $Hindu \times Muslim$ takes the same values across states, however, there is reason to believe that this effect may vary by state. The literature on the determinants of communal violence can reasonably be divided between the factors that trigger violence and the factors that constrain violence. As discussed in the introduction, elite manipulation (Brass, 2003) and negative growth shocks (Sergenti and Thomas, 2005) can create tension and trigger violence whereas police competence (Rai, 1999) and informal institutions that promote Hindu/Muslim interaction can constrain violence (Varshney, 2002). If we would like to incorporate religious holidays into this framework, we could observe that a month in which both a Hindu and Muslim holiday take place does not necessarily force violence to occur, it merely holds the potential for communal violence; and the particular characteristics of a state may determine whether violence does indeed break out. We replace $Hindu \times Muslim$ with 16 triple interaction variables to allow for this possibility (one for each state). Formally, the OLS specification is

$$v_{s,d} = \beta_0 + \phi z_{s,d} + \gamma h_{s,d} + \alpha_s + \delta_d + \omega p_{s,d} + \sum_{i=1}^{16} \rho_i H_{s,d} \times M_{s,d} \times State_i + \epsilon_{s,d}$$

The results of the above regression are in table 6. Column (1) contains the OLS specification with day, month, year and state controls and indicates that the effect of a month with both a Hindu and Muslim holiday on communal violence is significant and positive in some states (Andhra Pradesh, Bihar, Gujarat, Karnataka, Maharashtra, Rajasthan, Uttar Pradesh and West Bengal) and is insignificant in other states (Assam, Jammu and Kashmir, Kerala, Punjab, Tamil Nadu).

The fact that the interaction triggers violence in some states and not in others is interesting for several reasons. First, the distribution of incidents of communal violence is not uniform across all of India - instead violence is concentrated in a few states. If we compare this distribution with the t-statistics of the coefficients on the interaction for each state in the OLS regression, we see similarities (Figure 1). Gujarat (GU), Uttar Pradesh (UP) and Maharashtra (MA) have both a large amount of violence and have violence triggered during months of Hindu and Muslim holidays. If these months are periods of time when violence has the potential to be triggered, then the states that have riots during these particular months are also the states that have higher levels of rioting in general. Note that these t-statistics are from regressions with state controls and so this effect is not simply due to the fact that, for instance, in some states there are higher levels of violence. Additionally, the high t-statistic for Gujarat is ominous because the data ends in 1990, 12 years before the massive riots of 2002.

Although the above result is interesting, I attempt to partially explain it by testing to determine if violence is "functionally useful" to a political party in these states. I first test if the vote share of the dominant party of this period, the Congress Parties, is affected by violence in the period before an election. The results of these regressions are in table 8 below.

Column (1) contains the OLS specification with state controls. The positive and signifi-

Table 3.6: Effect of Religious Holiday Interactions on Communal Violence

	OLS	IV-2SLS	NegBin
$Hindu \times Muslim \times AP$	0.0015***	0.0016***	0.4498***
	(0.0003)	(0.0003)	(0.0851)
$Hindu \times Muslim \times AS$	-0.0014***	-0.0005	-1.2212***
	(0.0004)	(0.0003)	(0.1713)
$Hindu \times Muslim \times BI$	0.0019***	0.0021***	0.3215***
	(0.0003)	(0.0003)	(0.0802)
$Hindu \times Muslim \times GU$	0.0052***	0.0049***	0.2786***
	(0.0005)	(0.0005)	(0.0509)
$Hindu \times Muslim \times HA$	0.0007*	(omitted)	14.8457***
	(0.0003)		(1.0378)
$Hindu \times Muslim \times JK$	-0.0010**	-0.0012***	-0.4372***
	(0.0004)	(0.0004)	(0.0820)
$Hindu \times Muslim \times KA$	0.0041***	0.0046***	0.6316***
	(0.0003)	(0.0003)	(0.0934)
$Hindu \times Muslim \times KE$	-0.0003	-0.0005	-0.2290***
	(0.0004)	(0.0004)	(0.0705)
$Hindu \times Muslim \times MP$	0.0013***	0.0009**	0.1789*
	(0.0003)	(0.0004)	(0.0983)
$Hindu \times Muslim \times MA$	0.0027***	0.0034***	0.2431***
	(0.0003)	(0.0003)	(0.0405)
$Hindu \times Muslim \times OR$	0.0002	-0.0002	0.0061
	(0.0003)	(0.0004)	(0.0803)
$Hindu \times Muslim \times PU$	-0.0002	-0.0002	-0.0309
	(0.0005)	(0.0004)	(0.0717)
$Hindu \times Muslim \times RA$	0.0008**	0.0012***	0.4251***
	(0.0004)	(0.0004)	(0.1010)
$Hindu \times Muslim \times TN$	-0.0007*	-0.0005	-0.6836***
	(0.0004)	(0.0004)	(0.0826)
$Hindu \times Muslim \times UP$	0.0042***	0.0062***	0.4657***
	(0.0003)	(0.0003)	(0.0651)
$Hindu \times Muslim \times WB$	0.0013***	0.0015***	0.2172***
	(0.0003)	(0.0003)	(0.0723)
Political Religious Socioeconomic Controls	yes	yes	yes
Day Month Year State Controls	yes	yes	yes

Robust standard errors clustered at the state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Effects of Violence Before Elections on Vote Share for Congress Parties

	OLS	OLS	OLS	IV-2SLS
Congress Share$_{t-1}$	-0.13	-0.10	-0.11	-0.09
	(0.07)	(0.08)	(0.13)	(0.01)
SDP Growth × Inc. Congress	160.67**	160.73**	177.30**	290.01
	(57.61)	(60.28)	(66.33)	(215.00)
SDP Growth × Non-Inc. Congress	-188.70***	-195.70***	-92.37*	-206.35
	(47.35)	(52.61)	(51.41)	(152.97)
Violence$_{t-1}$	22.56***			
	(6.57)			
Violence × AP		-7.61	-8.69	-29.84
		(8.18)	(23.63)	(22.74)
Violence × GU		15.69***	8.90	11.87**
		(1.53)	(6.46)	(4.77)
Violence × HA		44.47***	50.76	(omitted)
		(7.67)	(59.28)	
Violence × KA		32.81***	52.38**	68.31***
		(4.23)	(21.30)	(19.11)
Violence × MA		44.80***	35.52*	42.33**
		(4.14)	(17.80)	(20.28)
Violence 2 Years Prior to Election	-2.52	-2.54	-2.98	-0.16
	(1.55)	(1.55)	(2.37)	(1.94)
State Controls	yes	yes	yes	yes
Year Controls	no	no	yes	yes

Robust standard errors clustered at the state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

cant coefficient on SDP Growth × Incumbent Congress realistically suggests that if Congress is the incumbent party and state domestic product grows in the year of an election, then it will translate into electoral gains; similarly, if Congress is not the incumbent party and state domestic product grows in the year of an election, then Congress will likely lose vote share. Violence in the month before an election increases vote share while violence in a long window before the election has no significant effect. Column (2) interacts the violence variable with state indicators to determine in which states this effect occurs. Since violence in the month before an election does not occur in all states, many of these interactions are omitted. The results suggest that when there is violence in the month before an election, vote share significantly increases in Gujarat, Haryana, Karnataka and Maharashtra. Gujarat, Karnataka and Maharashtra are 3 of the 4 states which have violence triggered during months of Hindu and Muslim holidays. Column (3) includes year indicators and column (4) is an instrumental variables regression to account for the potential endogeneity of the SDP growth interactions. For some inexplicable reason the coefficients on the SDP interactions become insignificant in the IV specification.

Next I run the same specifications with the dependent variable being the rival Janata Parties. The results are in table 9. Column (1) contains the OLS specification with state controls. The negative and significant coefficient on SDP Growth × Incumbent Congress realistically suggests that if Congress is the incumbent party and state domestic product grows in the year of an election, it will translate into electoral losses for the opposition party. Violence in the month before an election decreases vote share while violence in a long window before the election has no significant effect. Column (2) interacts the violence variable with state indicators to determine in which states this effect occurs. Since violence in the month before an election does not occur in all states, many of these interactions are omitted. The results suggest that when there is violence in the month before an election, vote share significantly decreases in Gujarat, Haryana, Karnataka and Maharashtra. Gujarat, Karnataka and Maharashtra are 3 of the 4 states which have violence triggered during months of Hindu and Muslim holidays. Column (3) includes year indicators and column (4) is an instrumental variables regression to account for the potential endogeneity of the SDP growth interactions. The coefficients on the SDP interactions become insignificant in the IV specification.

The results in tables (7) and (8) require an explanation because the Congress party is often seen as the more secular, tolerant in the Indian political arena. First, the elections which have violence in the preceding month are almost entirely elections in the 1980s and early 1990s - therefore it is useful to understand the political history of the Congress and Janata blocks during this period. Congress had been the dominant party until the late 1970s when the Janata coalition dramatically increased its vote share. Several authors describe a shift in Indira Gandhi's (the leader of the Congress Party) strategy in response to the changing political scene. Engineer writes, "The ruling Congress ... began exploiting ... the Hindu communal sentiments in its favour. This happened when she realised (in the post-Emergency period) that the Muslims would no longer vote *en bloc* for her party. The perceptible change in her behaviour could be observed after the Moradabad riots in 1980..."

Table 3.8: Effects of Violence Before Elections on Vote Share for Janata Parties

	(1)	(2)	(3)	(4)
Janata Vote Share$_{t-1}$	0.1106	0.1316	0.0897	0.3520
	(0.1134)	(0.1170)	(0.1231)	(0.4424)
SDP Growth × Inc. Congress	-174.0208*	-177.1918*	-121.0880*	-503.0471
	(88.6325)	(92.3095)	(63.9809)	(547.1689)
SDP Growth × Non-Inc. Congress	32.6084	38.7509	-23.2113	-331.2989
	(59.3765)	(64.0679)	(72.8490)	(329.0953)
Violence$_{t-1}$	-16.3543*			
	(8.2032)			
Violence × AP		-3.9268	28.9308	16.7080
		(4.1448)	(29.2400)	(31.7817)
Violence × GU		-8.8339***	-11.5320*	-14.0153**
		(2.3518)	(5.4932)	(7.0051)
Violence × HA		-27.7551***	-8.4027	(omitted)
		(6.3127)	(16.4214)	
Violence × KA		-35.0441***	-49.2270**	-61.4881*
		(5.9585)	(21.3610)	(35.9466)
Violence × MA		-18.6030***	0.4385	-9.7408
		(2.8629)	(13.3303)	(29.7683)
Violence 2 Years Prior to Election	-2.1965**	-2.2740**	-0.7909	-0.8807
	(0.8188)	(0.8385)	(0.8899)	(1.8950)
State Controls	yes	yes	yes	yes
Year Controls	no	no	yes	yes

Robust standard errors clustered at the state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(Engineer, 1989) Gulatti similarly describes how “the Congress party indulged in communal politics in order to retain its vote bank ...” (Gulatti, 2005) while Singh explains “when she [Indira Gandhi] again returned to power in 1980 ... Mrs. Gandhi manoeuvred the Congress to be the main beneficiary of the rising tide of Hindu communalism” (Singh, 2007). These explanations do help to clarify why violence before particular elections seems to be associated with electoral gains for the Congress party and electoral losses for the opposition.

3.5 Conclusion

In this paper I contribute to the literature on the determinants of religious violence and, in doing so, I suggest that violence before an election is associated with electoral gains and losses for different political parties. Initially I attempt to determine if religious holidays affect communal violence and understandably find an effect. The more puzzling finding is that violence is triggered in some states and not in others during months with both a Hindu and Muslim holiday. I interpret this finding by appealing to political scientist Paul Brass' statement that communal violence persists because it is ‘functionally useful.’

If violence persists in certain states because of the underlying usefulness, I look for the political usefulness by asking whether violence can affect electoral outcomes. My analysis suggests that in many of the states which have the largest, significant increases in violence during months of Hindu and Muslim holidays there are electoral gains when there is violence before an election. I attribute the electoral gains for the party Congress to changing political strategies during the 1980s as several authors suggest that Congress began to use communal tensions during this period.

Of course, this result is not a complete explanation for the variation in communal violence. If there are only gains to violence preceding an election in certain states, then we should not find violence at other points in time for any state. I instead interpret the vote share results as results which point to more fundamental differences between states. If we consider a framework for communal violence in which there are factors that promote violence (like political agents) and factors that constrain violence (like the police or associational institutions), then states likely differ considerably along these dimensions.

For example, the simple fact that religious holidays (as well as the Hindu and Muslim holiday interaction) are significant in a regression with data over 30 years is a damaging result for the police system. One would expect that police would determine that this pattern exists and attempt to minimize the damaging effects of religious holidays. Unfortunately, there is considerable evidence that the largely Hindu police are biased during incidents of communal violence (Rai, 1999). There is also mention of “politically motivated transfers of upright officers in riot prone Gujarat” (Sinha, 2005).

The literature so far tends to focus on one characteristic like medieval trade associations or political determinants of communal violence, but further research to model this violence which incorporates each result would provide new insights into the religious violence question.

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