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THE INVESTMENT AND INSURANCE EFFECTS OF UNRELIABLE ELECTRICITY: EVIDENCE FROM INDIAN MANUFACTURING

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To my partner, Karen, and family, Hina, Aravind, and Vidushi. For their ever-present love and support.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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ABSTRACT

Although unreliable electricity is a substantial burden on producers in India, the long-run effects of electricity shortages have received little attention. In this study, I study the long-run output and welfare costs of electricity shortages by examining the dynamic investment responses of producers. Specifically, I examine two dynamic margins of adjustment: (1) investment in productive capital, and (2) adoption of generators as insurance against these shocks. Using state-level power-sector data and plant-level manufacturing data from India, I document descriptive evidence that electricity shortage shocks depress investment by reducing the utilization of inflexible inputs. Furthermore, while plants that adopt generators mitigate the investment effects of energy shocks, they invest less in productive capital. I rationalize these patterns using a partial equilibrium model of investment dynamics augmented with electricity shortage shocks, costly generator adoption, and interactions between both dynamic margins. I estimate my model for two states - Maharashtra and Punjab - and find that electricity shortages are responsible for long-run value-added losses of 52% and 64% along with producer surplus losses of 44% and 57%. The dynamic losses are 2.5 to 3.5 times as large as the static value-added losses of 14% and 24%. However, these long-run losses are mostly ameliorated under a counterfactual dynamic pricing policy that adjusts electricity prices to prevent shortages. With dynamic prices, the long-run losses are reduced to just 5% and 13% for value added, and 4% and 11% for producer surplus. Finally, generator adoption undoes the "wait-and-see" effects of shortage uncertainty, though the former distorts the long-run firm size distribution.

CHAPTER 1

INTRODUCTION

As in many developing countries, electricity has historically been scarce and unreliably provided in India. As a result, power outages burden Indian firms, disrupting their economic activity and constraining their growth. According to the World Bank Enterprise Survey, electricity supply was reported as the most severe obstacle to growth by 33% (15%) of plants in 2005 (2014).[1] Hence, poor electricity supply could be a substantial friction to industrial growth, even more so than other frictions that have received widespread attention from researchers, such as corruption, credit constraints, taxation, and labor regulations. However, though electricity shortages have been shown to have negative effects in the short-run, the dynamic effects have received little attention. Since electricity shortages are a persistent feature of the Indian economy, firms might respond dynamically by adjusting their investment behavior, leading to differences between the short-run and long-run effects.

In this research, I seek to answer two questions: (1) How do electricity shortages affect firm investments? and (2) How do these investment responses affect long-run output and producer welfare? Specifically, I study manufacturing plants' simultaneous responses along two distinct dynamic investment margins - investment in productive capital as a channel for growth, and investment in backup generators as insurance capital.

On the surface, the direction of dynamic responses along each margin seems to be straightforward. For example, because capital is fixed in the short-run, shortages realized as blackouts may reduce the utilization of and therefore the return to capital. Therefore, plants may choose to invest less in productive capital if they expect high shortages in the future. Similarly, plants should choose to invest in backup generators to insure against future shortages. However, the plants' optimal responses become ambiguous when considering the simultaneity of choices along both investment margins. Generator adoption could comple-

1. See Table A.1 for a comparison of the severity of various frictions, and Figure A.1 for how severe an obstacle electricity is.

ment investment in productive capital by mitigating the adverse effects of future shortages, but could also discourage or crowd out such investment if generator costs reduce expected profits and consequently the returns to investment. These investment decisions, being dynamic, are potentially further complicated by irreversibilities and adjustment frictions along each margin. Altogether, the overall response depends not only on the distribution of future shortages and expected profits, but also on the costs of investment and generators. For convenience, I use "investment" to refer only to investment in productive capital going forward, distinguishing it from the adoption and ownership of generator capital.

I approach answering the research questions in two steps. First, I conduct a descriptive analysis, documenting suggestive evidence for the effects of electricity shortages on plant investments. I also document patterns suggestive of the interactions between generator adoption and productive capital investments. In the second step, I develop and estimate a partial equilibrium model of investment dynamics. I then use the estimated model to quantify the long-run effects of shortages on value added and producer welfare, as well as to evaluate counterfactual policy outcomes.

To conduct the descriptive analysis, I make use of India's official plant-level microdata, the Annual Survey of Industries (ASI). A challenge I face is that electricity shortages are not typically observed at the plant level. As shortages are not reported in the ASI, I instead make use of state-level electricity shortage data compiled by the Central Electricity Authority.[2] The CEA does not keep electronic records of its historical data, so I hand-collected and digitized the required data from their physical archives for use in this study. I combine the CEA data with the ASI and use this merged dataset for the descriptive study.

Two striking patterns emerge from my analysis of the combined ASI-CEA panel. First, plants without generators invest less, on average, when contemporaneous shortages are high. Plants with generators also invest less when shortages are high, though intuitively they

2. The CEA is the central government agency in India that collects and publishes energy-sector statistics for the country as part of its official responsibilities. Its shortage measure was also used by Allcott et al. (2016). More details are provided in chapter 3.

still invest more than plants without generators. Because investment is a dynamic outcome, these findings suggest that plants use contemporaneous shortages to form expectations about future shortages. To shed light on the mechanism, plants without generators utilize their capacity less during high shortage periods, whereas plants with generators do not.

Second, I study the direct relationship between generator ownership and investment. I begin by documenting the reversibility of generator ownership, which allows me to examine within-plant differences in investment behavior. Building from this observation, I find that, conditional on contemporaneous shortages, plants invest less, on average, during periods of generator ownership relative to periods without generators. This result indicates the presence of generator ownership costs that discourage further investment in productive capital, despite generators seemingly mitigating the adverse effects of electricity shortages on investment.

Motivated by my descriptive findings, I develop a partial equilibrium model of investment and generator-adoption dynamics. The model is specified to identify costs of investment and generator ownership that are consistent with investment and generator dynamics in the microdata. The model then allows me to evaluate counterfactual investment behavior, output, and producer welfare in the absence of electricity shortages, leading to estimates of the long-run costs of shortages. Furthermore, the model also allows me to evaluate the same outcomes under different electricity shortage and policy environments.

I build on a canonical model of plant-level investment dynamics by augmenting it with electricity shortage shocks and partially irreversible generator ownership. In the model, plants are exposed to two types of exogenous shocks, productivity and electricity shortage shocks, the latter of which affects capacity utilization. Both types of shocks are persistent, and plants use contemporaneous shock realizations to form expectations about future shocks. In response, plants simultaneously choose to invest in productive capital (a continuous choice) and own a generator (a discrete choice). To capture the responsiveness of capital to shocks, plants face adjustment frictions when changing their capital stock. Plants also face sunk adoption costs and recurring maintenance costs of generator ownership; the former captures the partial irreversibility of generator adoption, and the latter allows for generator ownership to affect profits and investment choices. Finally, plants' profits are derived from an underlying model of production that follows Allcott et al. (2016), allowing the model to speak to output and producer welfare outcomes.

I then proceed with the estimation of the model, relying on institutional features of India's electricity markets to inform the appropriate level of estimation. In India, retail electricity market operations and regulation tend to be localized at the state-level. As a result, the distortions responsible for shortages and therefore the shortage shocks themselves vary idiosyncratically by state. Hence, I estimate the model at the state level, specifically for two states: Maharashtra and Punjab.

For each state, estimation proceeds in three steps. First, I estimate the static profit functions and productivity using a combination of the static model and production function techniques from the industrial organization literature. Next, I estimate the shock process for electricity shortages using novel monthly frequency shortage data from the CEA. Last, I estimate the "dynamic" parameters (specifically, the capital adjustment and generator costs' parameters) using the Simulated Method of Moments. In particular, I estimate a rich specification of adjustment and generator costs that match investment- and generator-related moments from the microdata.

The model estimates reveal that generator costs are quantitatively important for plants. Recurring fixed costs of generator ownership drive economies of scale in generator adoption, leading to a positive correlation between generator ownership and size.[3] Recurring generator variable costs are sizable in magnitude, reducing profitability (9-10% in both states) and consequently the returns to investment. These variable costs suggest that generator adoption likely does crowd out investment in productive capital. Generator adoption costs are also quantitatively large, suggesting partial irreversibilities play a role in plants' self-generation

3. This finding is consistent with those in much of the literature on generator adoption. See, for example, Foster and Steinbuks (2009).

choices. Finally, the costs of capital adjustment include both non-convex and convex components, consistent with the literature on investment dynamics and adjustment frictions (e.g., Cooper and Haltiwanger, 2006).

Next, I quantify the long-run costs of electricity shortages by evaluating the investment behavior, output, and producer welfare in a counterfactual economy with no electricity shortages. As I evaluate outcomes for the stationary distributions of the estimated and counterfactual economy, differences in aggregate outcomes should be interpreted as long-run differences. The implied long-run costs of electricity shortages are substantial: Compared to the shortage-free counterfactual economy, value added is 52.27% and 63.64% lower in Maharashtra and Punjab, respectively. These aggregate output effects highlight the importance of dynamic margins in evaluating the full burden imposed by electricity shortages. In contrast, if capital choices were assumed to be exogenous, the long-run "static" losses amount to 13.98% and 23.75% of output. Although still sizable on their own, these short-run effects (as implied by Allcott et al., 2016) are amplified by dynamic adjustments, leading to much larger long-run effects. Further, these results also highlight the importance of studying investments in productive and insurance capital simultaneously. To illustrate, if all plants owned generators, the contemporaneous shortage losses would be minimal, but the long-run losses could still be large due to the crowding out of productive capital by generator capital.

The long-run losses I estimate are benchmarked against a stylized economy that assumes no shortages, holding electricity prices constant. To study a more realistic policy, I then conduct a counterfactual dynamic pricing exercise in which I allow deregulated electricity prices to clear electricity markets and prevent shortages.[4] Intuitively, dynamic pricing should be less costly for manufacturers because electricity is a quantitatively small share of production costs, and the counterfactual outcomes confirm this intuition. Dynamic pricing mostly alleviates the burden of shortages on manufacturers, reducing value added and producer surplus

4. In India, electricity tariffs are regulated and tend to be very rigid, changing at approximately annual frequencies. See chapter 2 for a more detailed discussion about the electricity pricing environment in India and how electricity prices aren't market-clearing prices.

losses to 4.96% and 4.03% in Maharashtra, and 13.46% and 11.45% in Punjab (relative to the stylized shortage-less economy). Although dynamic pricing faces regulatory and infrastructure barriers to implementation in India, the magnitudes suggest that a shift to such a policy would greatly benefit producers in the long run.

Last, I study the potential impact of uncertainty about future shortages. When investments are (partially) irreversible, uncertainty in general increases the option value of waiting, leading to delayed investments and increased inaction.[5] However, the effects of uncertainty about future shortages may not conform to this pattern due to the presence of two separate and irreversible margins of investment, the returns to which vary in opposing directions with shortages. Hence, the effects of shortage uncertainty (i.e., the volatility of expected future shortages) merit attention, particularly given the second investment dimension of insurance capital.

Perhaps counterintuitively, a reduction in uncertainty to zero (or an economy with a constant shortage level over time) leads to decreases in value added and producer surplus in both states (relative to the estimated economies). This effect can be rationalized by the fact that higher volatility places more weight on better (low) shortage states when the average shortage is low enough, benefiting producers. However, higher volatility levels place more weight on extreme bad (high) shortage states, which leads to more investment inaction but greater generator adoption. In aggregate, as uncertainty becomes larger, greater generator ownership undoes this "wait-and-see" effect for productive capital, though at a cost. Given high shortage uncertainty, plants are incentivized to own generators and reluctant to relinquish them. As a result, plants have a distorted incentive to stay large given the fixed costs of self-generation, and though output is higher for this reason, producer welfare suffers.

This text contributes mainly to the following lines of literature. First, it contributes to the literature studying the economic effects of electricity supply (on the access, shortages, and pricing margins) on firm behavior. A large part of this literature studies the static

5. See Dixit and Pindyck (1994).

effects of electricity shortages. In an influential paper (particularly for this study), Allcott et al. (2016) find that electricity shortages in India cause substantial revenue and producer surplus losses in the short-run.[6] I contribute to this literature by developing a model of joint investment and generator dynamics, and using it to estimate long-run output and welfare effects of electricity shortages. Among the rest, only a few papers study the investment effects of electricity shortages.[7] I contribute to this literature by studying two margins of investment - productive and insurance capital - jointly in a dynamic setting.

This study also contributes to the broad literature studying the misallocation of inputs and the associated implications for aggregate productivity (see Restuccia and Rogerson, 2017, for a comprehensive survey). Some studies indirectly quantify the total misallocation of labor and capital in various economies, while others focus on misallocation due to specific frictions.[8,9] Closer to the latter set, this study contributes by quantifying the degree to which electricity shortages, a distortion that has received relatively less attention and is directly manipulable by policy, affects the allocation of resources across producers in India. In particular, this work captures misallocation on both the intensive margin (the effect of shortages on the allocation of productive capital) and extensive margin (generator ownership as a technology choice).

6. Other studies include Fisher-Vanden et al. (2015), who find that Chinese firms outsource the production of electricity-intensive intermediate inputs as a response to electricity shortages.Cole et al. (2018) conduct a similar exercise for a number of African countries. Alam (2013) finds that responses to power shortages vary by industry.

7. Abeberese (2019) finds that a period of planned electricity rationing in Ghana led to lower levels of investment by manufacturing plants. Reinikka and Svensson (2002) use a cross-section of Ugandan establishments and find that in a static setting, electricity shortages lead to lower investment in capital and greater generator adoption. Alby et al. (2013), Rud (2012b), Steinbuks and Foster (2010) and Foster and Steinbuks (2009) study investment in self-generation by firms in static frameworks, abstracting away from other forms of capital.

8. Examples include Banerjee and Duflo (2005), Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Petrin et al. (2011) and Bartelsman et al. (2013).

9. Some examples include credit constraints (Gilchrist et al., 2013; Midrigan and Xu, 2014; Moll, 2014), information frictions (David et al., 2016), trade policy (Khandelwal et al., 2013), and contracting frictions in intermediate input markets (Boehm and Oberfield, 2018), among others. A few papers also study misallocation in conjunction with adjustment frictions, such as the aforementioned David and Venkateswaran (2019) and Asker et al. (2014).

The next is the line of literature that characterizes capital adjustment frictions at the micro level to explain the responsiveness of investment to shocks.[10] On the other hand, an empirical literature studies firm investments in specific technologies or industries.[11] While methodologically closer to the former literature, this study contributes by highlighting that the nature of the shocks matters along with the simultaneity of investment in heterogeneous capital goods as well as by estimating a model that incorporates these features. A subset of this literature specifically examines the effects of uncertainty on investment behavior.[12] I contribute to this literature by studying and estimating, to my knowledge, one of the first dynamic models of a natural setting with uncertainty (in future shortages) and endogenous insurance (generators).

The rest of this text proceeds as follows. Chapter 2 provides some background on the Indian electricity markets and regulatory environment, describing the sources of electricity shortages. Chapter 3 describes the data used for this study. Chapter 4 provides suggestive evidence of the mechanism posited by this study. Chapter 5 details the model of investment dynamics with electricity shortages and generator adoption, and chapter 6 describes the estimation of the model and reports the resulting estimates. Chapter 7 details counterfactual analyses, and chapter 8 concludes.

10. For example, David and Venkateswaran (2019), Asker et al. (2014), Cooper and Haltiwanger (2006), Cooper et al. (1999) and Caballero et al. (1995) study adjustment costs and their aggregate implications for capital goods in general. A related literature also attempts to characterize labor adjustment frictions to explain hiring behavior observed in microdata. See Bond and Van Reenen (2007) for a survey.

11. Some examples include Igami (2017) for hard disk drives, Schmidt-Dengler et al. (2006) for MRI adoption by U.S. hospitals, and Kalouptsidi (2014) for the shipping industry.

12. Examples include Bloom (2009) and Bloom et al. (2007). In an energy context, Kellogg (2014) studies the effect of oil price uncertainty on drilling activity while Johnston (2018) studies the effect of electricity price uncertainty on manufacturing investment.

CHAPTER 2

BACKGROUND AND INSTITUTIONAL DETAILS

As recently as the summer of 2012, the world's largest ever blackouts struck the Indian economy. Spanning over two days and twenty two states, the blackouts left over 600 million people without access to electricity. Although not usually on the same scale, power outages have historically been a frequent occurrence for Indian electricity consumers, adversely affecting day-to-day economic activity. These persistent energy shortfalls are symptomatic of a combination of inadequate infrastructure and regulatory barriers that prevent electricity markets from clearing, leading to persistent excess demand across the country.

The sources of shortages can be traced primarily to the tariff constraints and sub-par performance of state-owned utilities. Although private participation has increased in recent years, the state and central governments have historically been responsible for the majority of electricity supply in India, with publicly generated electricity accounting for an average of 86% of annual electricity production for the period 1998-2012.[1] State government-owned utilities in particular play the major role in the generation, transmission, and distribution (i.e., sale to final consumers) of electricity, supplying 60% of electricity and being the only retail distributors of electricity in their respective states.[2] Although certain generation-related inefficiencies contribute to India's shortage problem (such as under-utilization of capacity, coal shortages for thermal plants and poor management; see Chan et al., 2014; Malik et al., 2015), the primary bottlenecks to electricity provision lie with the state-owned distribution companies and the rigid retail tariffs.

Distribution companies face major constraints in the form of distorted tariff structures. In my sample period, tariffs were set either by vertically integrated state utilities (State Electricity Boards) that owned distribution companies or state-specific electricity regulatory

1. Generation and supply statistics are sourced from the "General Review" (1998-2012) published by the CEA.

2. As of 2012, only Delhi and Orissa had fully privatized distribution. Source: "Report on the Performance of State Power Utilities for the Years 2010-11 to 2012-13" published by the Power Finance Corporation.

commissions. Tariffs typically are rigid and change infrequently (on average, states adjusted tariffs once every three years), meaning that distribution companies cannot adjust electricity prices to clear the market. Furthermore, tariffs face downward pressure from the state governments that wish to keep electricity cheap for consumers. As a result, tariffs are too low for distribution companies to recover their costs, leading to quantitatively large gaps between average costs and average revenues (17% in 2006).[3] Altogether, the regulated tariffs effectively act as price ceilings, leading to excess demand for electricity.

Tariffs face downward pressure from state governments for primarily political motivations. Efforts to raise prices tend to be unpopular with voters, particularly farmers who often pay just a fixed fee (based on their electric pump capacity) and receive effectively unlimited access to grid electricity. Instead of raising tariff levels to clear the market, state governments pursue costly (and ultimately ineffective) policies of subsidization and cross-subsidization. Direct subsidies to distribution companies don't usually cover the entirety of their losses (after subsidies, the gap between average cost and average revenue still amounted to 9% in 2006). States also cross-subsidize low prices paid by agricultural and residential customers by charging industrial consumers higher electricity prices, which still isn't enough to cover distribution-company losses. Such losses are further exacerbated by theft, poor metering practices, and low-quality distribution infrastructure, which leads to high transmission and distribution losses (26% on average, compared to $< 6\%$ for the U.S. in the same period). Hence,

Having been in place for several decades, the distortionary tariff-setting, subsidization, and cross-subsidization policies have driven long-term losses and large debts for distribution companies, leaving them unable to purchase sufficient electricity to meet demand. Hence, despite substantial increases in generating capacity and a spate of power sector reforms, electricity shortages have remained a persistent and significant feature of the Indian economy.

3. Average cost and revenue statistics are sourced from the "Performance of State Power Utilities for the years 2006-07 to 2008-09" published by the Power Finance Corporation.

CHAPTER 3

DATA

I construct a merged panel dataset by combining manufacturing establishment data from India's official manufacturing survey, official electricity market statistics, and additional state-level aggregates. All financial quantities are deflated to 2004 Indian rupees (INR). Details on the sample selection and cleaning process are provided in Appendix B.

3.1 State-level Data

3.1.1 Power-Sector Data

The state-level power-sector data were obtained from a variety of documents published by the Central Electricity Authority (CEA) of India, forming a state-level panel at the annual frequency for the period 1998-2012.[1] Most of the source publications were only available as hard copies at the CEA, who maintained them as internal copies. Therefore, as in Allcott et al. (2016), much of the data were therefore obtained by scanning and digitizing relevant tables from these publications.

Electricity shortage data is collected from a publication called the "Load Generation Balance Report" (1998-2012) in which the CEA provides data about the electricity made available for consumption as well as an estimate of the energy requirement. Electricity shortages are then defined as the difference between the requirement and availability as a percentage of the requirement. While the CEA does not use an econometric model of electricity demand, according to CEA officials the energy requirement variable is retroactively updated using data reported by utilities on electricity consumption and load shedding (i.e. the connected load of consumers who lose access to grid electricity) as well as corrections for the quality of electricity, mitigating the need for an econometric model.

1. In fact, both the state-level data and the manufacturing microdata were collected annually for each fiscal year, which runs from April 1 to March 31 of the next year. Therefore, a year in this text refers to an Indian fiscal year, and reported years are the first year spanned by that fiscal year.

From the "General Review" publications, I obtained data on generating capacity and gross generation of electricity by state-owned, central government-owned, and privately owned power plants. In addition, I extracted data on electricity consumption (by type of consumer) as well as transmission and distribution losses from the same publications. Next, I collected average prices of electricity for various consumer groups (agricultural, industrial, domestic, and commercial) from a combination of "Electricity Tariff & Duty and Average Rates of Electricity Supply in India" and "Annual Report" publications by the CEA. Since states have widely varying tariff structures, I make use of average electricity costs to consumers for more comparable measures.

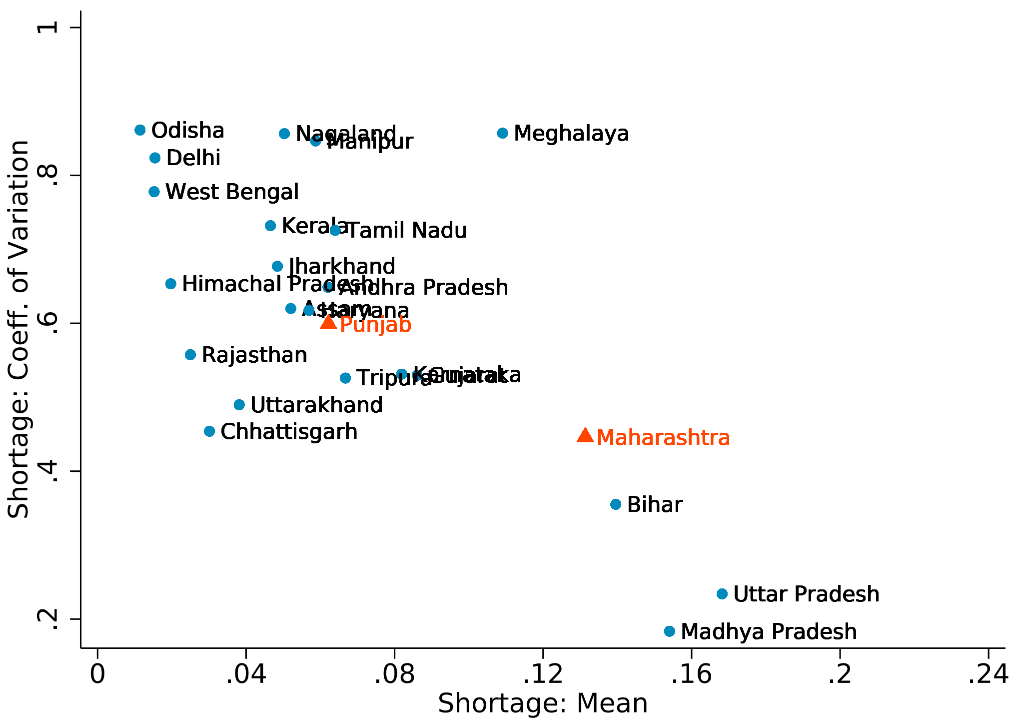
Lastly, I collected monthly frequency shortage data from "Power Supply Position - Energy" reports for the period 2006-2012 for use in the structural estimation. Importantly, the monthly shortage data are a disaggregated version of the aforementioned annual shortage data. Until recently, these monthly reports were primarily for the CEA's internal purposes and not for publication. As such, the CEA did not maintain either electronic or physical records of the monthly data prior to 2006.

3.1.2 State Variation in Shortages

Although explaining the source of shortages is not the focus of this study, an early examination of the shortage data suggests a study of the dynamic effects of shortages should be conducted at the state-level (or a finer level of aggregation). Figure 3.1 shows the unconditional mean and coefficient of variation for the CEA annual "shortage" series by state, and Figure 3.2 does the same for the monthly series.

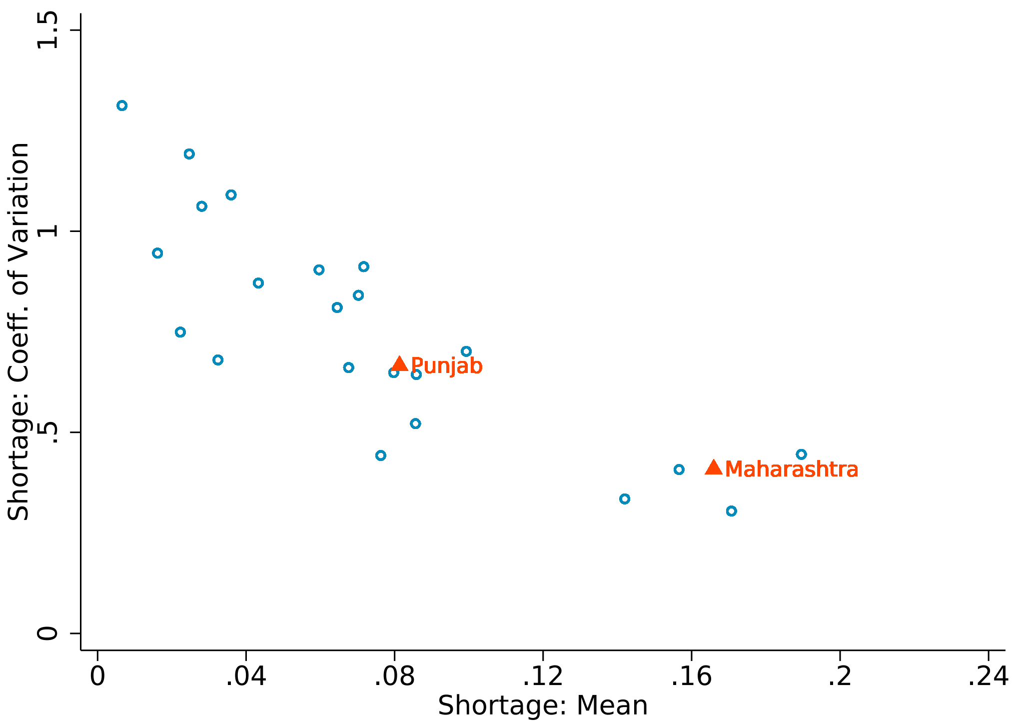
The shortage magnitudes immediately stand out as large, with some states experiencing shortages of over 10% on average. Comparing to responses from the 2005 World Bank Enterprise Survey, plants experienced an average (median) of 434 (200) hours. Then, a back-of-the-envelope calculation of 3,000 hours of operation implies an average (median) shortage of 14.5% (6.67%), suggesting that the CEA shortage magnitudes lie well within the

Figure 3.1: Mean and Coefficient of CEA "Shortage" Variable by State: Annual Frequency



Shows cross-sectional and intertemporal variation in shortages using annual shortage data for the period 1998-2012. Punjab and Maharashtra are highlighted. Means and coefficients of variation for Bihar, Madhya Pradesh and Uttar Pradesh are computed after they were split in 2001. Coefficients of variation computed as the standard deviation over the mean for each state.

Figure 3.2: Mean and Coefficient of CEA "Shortage" Variable by State: Monthly Frequency



Monthly cross-sectional and intertemporal variation in shortages using monthly shortage data from January 2006 to December 2012.

realms of reason.[2]

Both figures suggest that realized shortages vary substantially across states as well as over time within state, consistent with the fact that many of the underlying distortions responsible for these shortages are locally determined at the state level. To further understand the sources of variation in the shortage, I run the following regression for annual state-level shortages:

$$\text{Shortage}_{st} = \beta X_{s,elec} + \nu_s + \eta_t + \varepsilon_{st}, \tag{3.1}$$

where X_{st} is a set of state-level power-sector covariates including state government- and privately-owned capacity located within the state, central government-owned capacity in that state's region, reported transmission and distribution losses, price of agricultural and domestic electricity relative to industrial electricity, population and lagged gross state domestic product (GSDP).[3] Notably, none of these covariate measures are directly included in the computation of the shortage measure, ruling out mechanical correlations.

The results of the regression from (3.1) (reported in Table 3.1) yield one main takeaway - much of the variation in "shortage" comes from state-level factors. The coefficient signs are consistent with the discussion in chapter 2; as expected, shortages are decreasing in both state and central capacity, while they are increasing in T&D losses and the agricultural cross-subsidization (defined as the difference between the industrial and agricultural electricity prices, relative to the industrial price). The addition of aggregate shocks (year fixed effects) does not substantially improve the fit of the linear model. While region-year fixed effects do, the additionally explained variation is relatively small compared to the variation explained at the state level, reinforcing the notion that shortage variation is primarily state-specific.

2. I assume 300 working days (ASI mean and median of 287 and 302, respectively) and a conservative 10-hour working day.

3. Each state is in one of five regions: Northern, Southern, Eastern, Western, and North-Eastern.

Table 3.1: Explaining Variation in "Shortage"

	(1) Shortage	(2) Shortage	(3) Shortage
log(State Capacity)	-0.0231**	-0.0191*	-0.0223**
	(0.00997)	(0.00997)	(0.00927)
log(Central Capacity)	-0.0164	-0.0376*	.
	(0.0192)	(0.0205)	.
T&D Losses (%)	0.160***	0.155***	0.0517
	(0.0375)	(0.0387)	(0.0359)
$(p_{ind} - p_{dom})/p_{ind}$	-0.0485**	-0.0498**	-0.0498**
	(0.0216)	(0.0215)	(0.0193)
$(p_{ind} - p_{agri})/p_{ind}$	0.0521*	0.0510*	0.0340
	(0.0286)	(0.0287)	(0.0252)
log(Population)	0.302***	0.178**	0.246***
	(0.0639)	(0.0799)	(0.0757)
log(GSDP)$_{t-1}$	0.0398**	-0.0147	0.0145
	(0.0187)	(0.0338)	(0.0292)
Observations	337	337	337
Adj. R-squared	0.575	0.593	0.727
State FE	Yes	Yes	Yes
Year FE	No	Yes	No
Region-Year FE	No	No	Yes

Regression of "Shortage" on state-level covariates. For p_{agri}, p_{dom} and p_{ind} I use the average estimated rate of electricity supply for medium consumers in each group. Column (1) contains only state fixed effects, column (2) includes a year fixed effect while column (3) includes region-year fixed effects. Regressions also control for state splits individually (Bihar, Madhya Pradesh and Uttar Pradesh split in 2001). Since "log(Central Capacity)" is measured at the region-year level, it is excluded from the regression in column (3).

3.1.3 Additional Covariates

To complement the power-sector data in the descriptive analysis, I obtained data on the Gross State Domestic Product (GSDP) and population from the Ministry of Statistics and Programme Implementation (MOSPI). These data are identical to national accounting data, except they are reported at the state rather than the country level. I also collected state-level proxies for financial development from the Reserve Bank of India's Handbook of Statistics on the Indian Economy. In particular, I collected data on the number of bank branches and the aggregate credit-to-deposit ratio at the state level to proxy for credit market conditions at the state-year level.

3.2 Annual Survey of Industries

The Annual Survey of Industries (ASI) is administered yearly by the India's Central Statistics Office (CSO), and its scope includes all manufacturing establishments (henceforth interchangeably referred to as plants) registered under the Factory Act, 1948. The survey consists of two parts: a census of all large plants employing 100 or more workers ("census scheme") and a representative sample of smaller plants that employ between 10 and 100 workers ("sample scheme"). Census scheme plants are surveyed annually, whereas sample scheme plants are surveyed every three years, on average. I use the ASI data from 1998 to 2012; during this period, the data contains establishment identifiers that are consistent over time, forming an unbalanced plant-level panel. The baseline sample I use contains 405,639 plant-year observations, of which 178,757 are from the census scheme and 226,882 are from the sample scheme.

In the ASI, I observe the usual production data including revenues, employment, labor expenditures, and materials expenditures. Importantly, I also observe three key variables regarding electricity consumption. First, I observe electricity purchased and consumed (both quantity and expenditure), and I also observe the quantity of electricity self-generated and consumed. I use this latter variable to construct a proxy for generator ownership, defining a plant as a generator owner if it reports positive self-generation. I do not observe a generator capital stock, so generator ownership is defined as a dummy variable.

Regarding capital and investment, I observe the book values of capital at both the start and the end of the year. I also observe reported depreciation and gross capital formation during the year. I use the latter as my measure of investment, which is convenient given the unbalanced nature of the ASI panel. Furthermore, I observe the same variables for equipment capital specifically, and define the stock of non-equipment capital to be the total capital stock less the stock of equipment. I rely on the book value of capital (deflated to 2004 prices) due to sample scheme plants not being observed in consecutive years.[4]

Lastly, I also observe various measures of capacity utilization. I observe the reported number of working days, broken down into the number of manufacturing working days and non-manufacturing days. I also observe total man-days employed by the plant. I use the last measure to construct my preferred measured of utilization, as man-days per worker. Table 3.2 reports the summary statistics for the ASI data.

4. A perpetual inventory calculation of the capital stock would rely on assumptions on how investment was distributed between the two years a plant is observed. Given the lumpy nature of investment, such assumptions could introduce mis-measurement in computing the capital stock using such a method.

Table 3.2: Summary Statistics for ASI Plants 1998-2012

	Mean	S.D.	Min.	Max	Num. Obs.
Plant Observations	2.78	2.70	1	15	145359
Revenues (million INR)	168.6828	2658.888	.0014931	803637.6	405639
Employment	76.63201	372.0381	0	45901	405639
Labor Expenditure (million INR)	7.840332	75.54242	0	17603.92	405639
Materials Expenditure (million INR)	116.4404	2044.843	.0002088	628066.6	405639
Electricity Expenditure (million INR)	4.175155	52.17852	0	23505.04	405639
Electricity Purchased (kWh)	1075032	2.28e+07	1	9.60e+09	405639
Electricity Price (INR)	4.646859	3.694102	0	3683.887	405639
Electricity Self-Generated (kWh)	438552.4	2.09e+07	0	7.66e+09	405639
1(Generator)	.2866356	.4521904	0	1	405639
Opening Capital Stock (million INR)	42.60952	868.0255	0	509670	405639
Closing Capital Stock (million INR)	46.8262	918.0519	0	511058.8	405639
Investment Expenditure (million INR)	7.932626	233.0161	-2018.06	128869.8	393676
Depreciation (million INR)	4.750256	80.22839	6.57e-07	23049.42	393676
Opening Equip. Capital Stock (million INR)	35.04389	830.2604	-201.1761	509670	400229
Closing Equip. Capital Stock (million INR)	38.49352	876.1358	-167.516	511058.8	400229
Equip. Investment Expenditure (million INR)	6.621968	221.4088	-1960.256	117094.3	388690
Equip. Depreciation (million INR)	4.050546	76.32829	0	23049.42	388934
Man-Days Worked	23173.97	119751.9	0	1.64e+07	405639
Working Days	287.3005	50.74112	0	365	368210
Manufacturing Days	281.3062	57.2948	0	365	369764
Non-Manufacturing Days	6.372177	28.59707	0	365	371593
Age	111.5179	355.1611	0	2012	404707

Summary statistics for the ASI data 1998-2012. All statistics are weighted by provided sample weights. All financial quantities are deflated to 2004 Indian rupees (INR).

CHAPTER 4

DESCRIPTIVE PATTERNS AND EVIDENCE

In this chapter, I first document stylized facts about generator take-up and investment by manufacturing plants in India. I then conduct a regression analysis to first establish that the CEA's measure of shortages is informative of the actual shortages that plants face, following which I study the how plants' investment decisions vary with shortages and generator take-up. Lastly, I test two potential mechanisms through which electricity shortages could affect the returns to investment for plants.

4.1 Generator Patterns

Generator use by manufacturing plants in India is common, with 28.7% of plants reporting generating their own electricity in a given year. Generator ownershup is particularly high in larger plants, where 53% of plants with over 100 employees report self-generating electricity.[1] Figure 4.1 shows the rate of generator use by plant size.

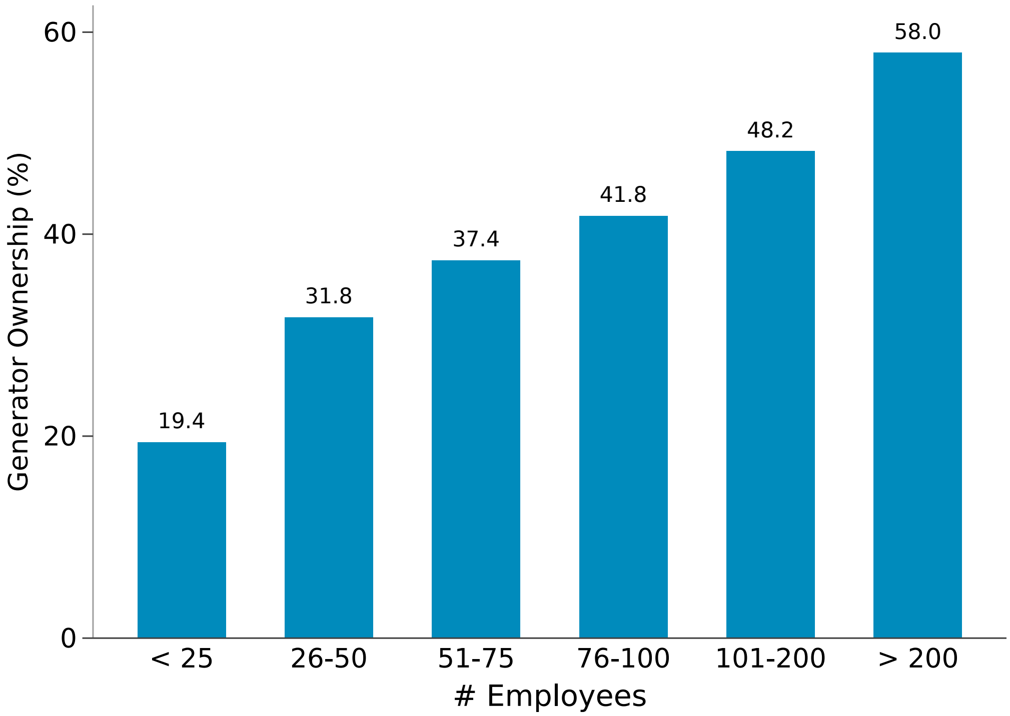
In addition, generator adoption is at least partially reversible, as substantial share of plants report not generating their own electricity having self-generated in the past. To illustrate, Figure 4.2 plots the weighted share of plants that adopt or remove a generator by year.[2] This fact is consistent with the partial irreversibility of capital goods in general, as instances of negative investment are reported in the ASI.[3] Furthermore, a generator rental market does exist in India, which could partially explain this pattern. Finally, though not direct evidence of such, a revealed preference interpretation of plant behavior does suggest the presence of recurring generator ownership costs that create an incentive for generator

1. This fact is consistent with findings from other studies on generator take-up. See, for example, Foster and Steinbuks (2009). Allcott et al. (2016) document the same for ASI plants.

2. A plant is a generator adopter if it self-generates in the current period while not having done so in the period it was last observed. Similarly, a plant removes a generator if it does not self-generate contemporaneously but did in the period it was last observed.

3. Approximately 5% of plant-year observations report negative investment.

Figure 4.1: Generator Use by Plant Size



removal.[4]

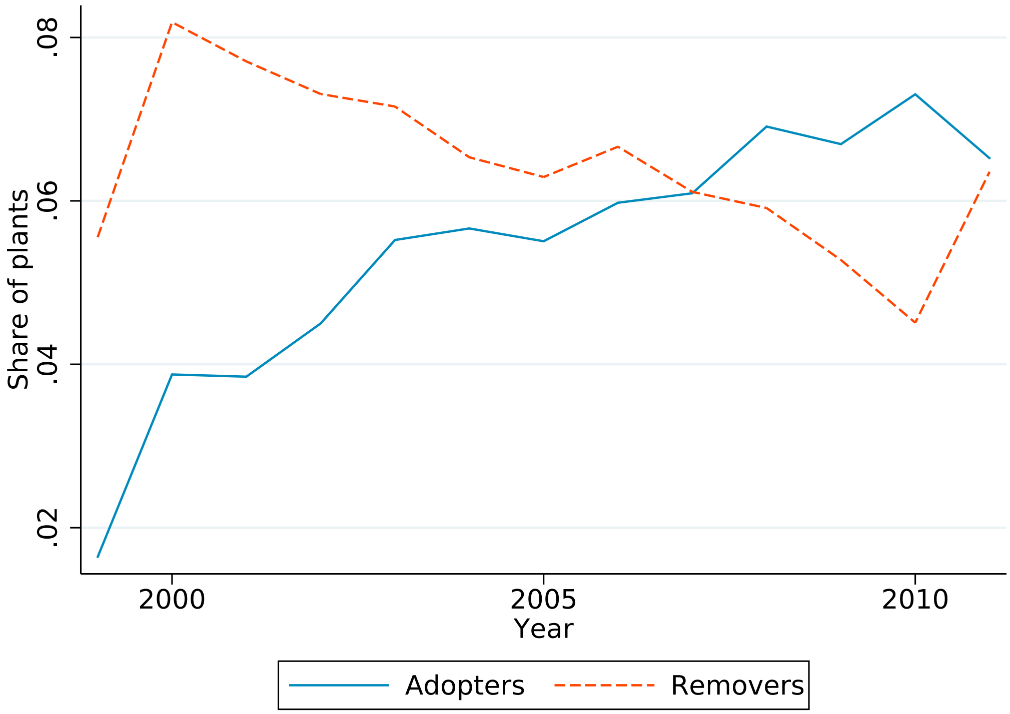
4.2 Investment Patterns

Figure 4.3 plots the distribution of the investment rate (defined as investment expenditures divided by the value of the capital stock at the opening of the year). An immediate standout feature is the high incidence of inaction; approximately 25% of plants report zero investment during a given year. In addition, the distribution of the investment rate is highly skewed, a general pattern that suggests the presence of both non-convex and convex adjustment frictions to capital (see, e.g., Cooper and Haltiwanger, 2006).

Differential investment behavior by plants with and without generators could also be informative of the differential returns to capital by generator ownership. Figure 4.4 plots the

4. Positive resale value on its own might be an incentive for plants to sell generators. However, this is unlikely given that generators are a depreciating asset and that empirically, plants' don't appear to have reason to expect considerably lower shortages in the future.

Figure 4.2: Generator Adoption and Removal Events by Year

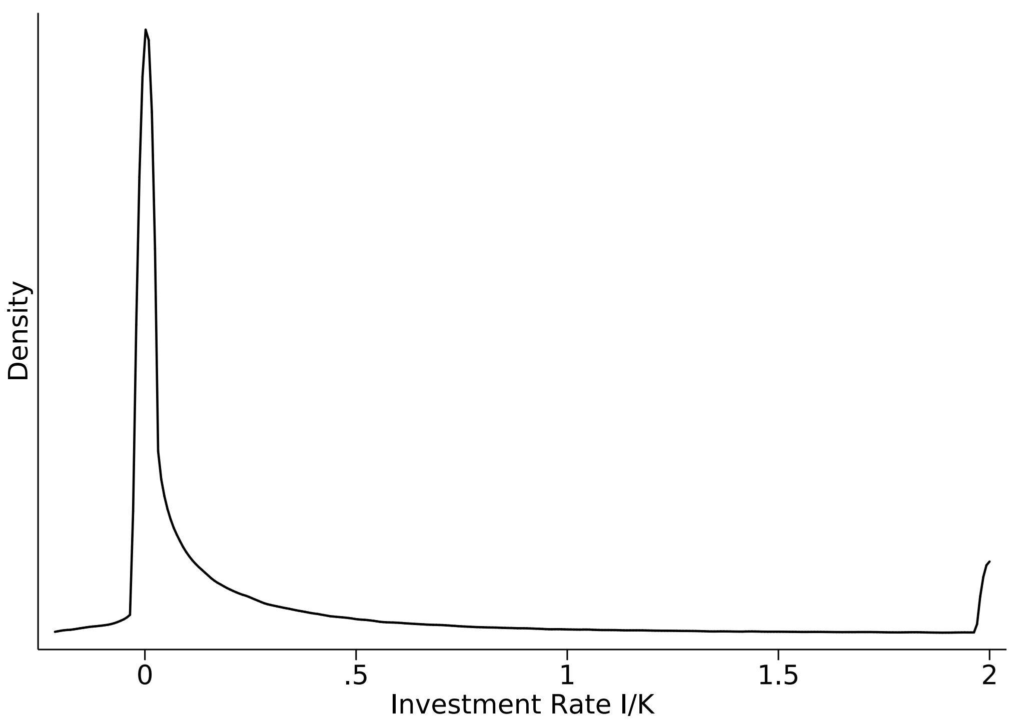


distributions of investment rate for plants by self-generating status and reveals such suggestive differences. Plants with generators invest more, on average, than plants without (28.2% vs. 23.9%), are less prone to inaction (12.3% vs. 30.4%), and more prone to large bursts of investment (defined as an investment rate greater than 20%; 36.2% vs. 28.7%). These differences support the fact that plants with generators are less exposed to negative electricity shortage shocks that lower the returns to investment, making plants with generators willing to invest more on both the extensive and intensive margins.

4.3 Regression Analysis

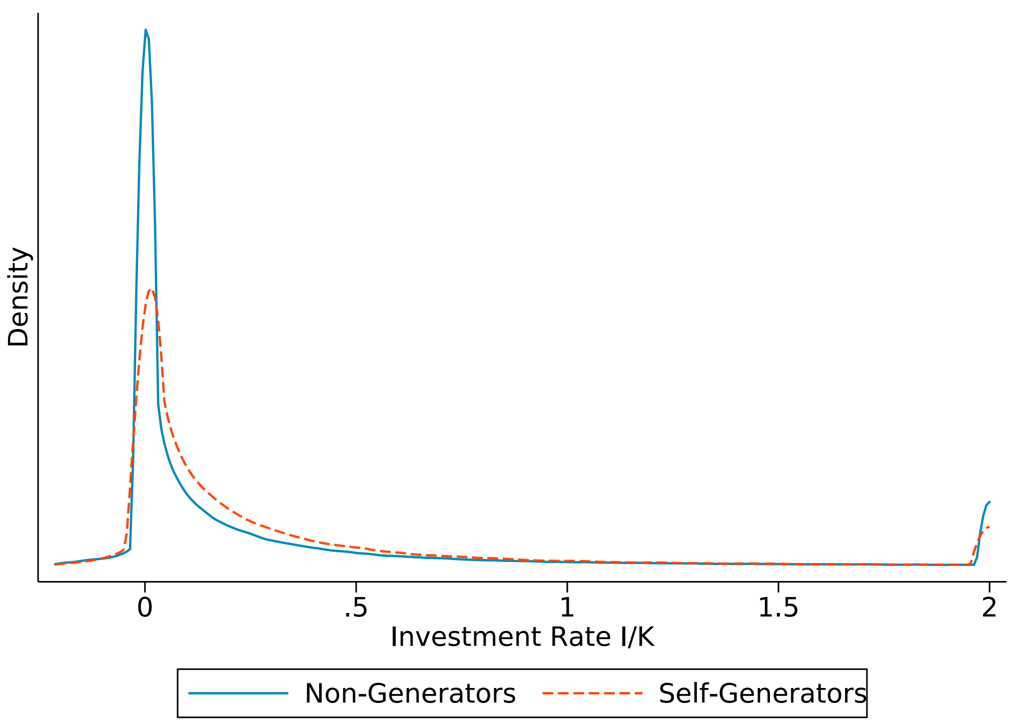
Although the heterogeneous investment behavior by generator ownership is suggestive of the negative effects of electricity shortages on investment and the role generators play in insuring against such shocks, it could still be reflective of the composition of firms that adopt generators or omitted variables. Therefore, I make use of the CEA shortage measure

Figure 4.3: Investment Rate Distribution



Kernel density estimates of the distribution of investment rate for ASI plants. Observations are weighted by provided sample weights.

Figure 4.4: Investment Rate Distribution



Kernel density estimates of the distribution of investment rate for ASI plants, by whether or not plant owns a generator. Observations are weighted by provided sample weights.

for a deeper and more robust analysis of how shortages may affect investment.

4.3.1 Validating the Shortage Measure

First, I provide evidence supporting use of the CEA's shortage measure for my analysis. Allcott et al. (2016) provide a substantial amount of evidence that strongly supports the usefulness of the CEA shortage measure. Nevertheless, though my data sources are the same, my sample periods are different, and therefore I supplement their findings by testing how electricity usage of the ASI plants varies with the shortage variable. In particular, I test how grid electricity usage and self-generated electricity vary with the shortage measure. I do so by running the following regression:

$$Y_{isjt} = \beta \, \text{Shortage}_{st} + \gamma X_{isjt} + \theta S_{st} + \nu_i + \lambda_{jt} + \varepsilon_{isjt}, \tag{4.1}$$

where Y_{isjt} is an outcome variable for plant i in state s and industry j in year t. Along with plant and industry-year fixed effects, I condition on plant-level covariates X_{isjt} and state-year covariates S_{st} in this specification. To avoid confounding with electricity price effects, I control for the plant-specific electricity price. I also control for plant age as well as state GSDP per capita and population to account for market size effects. Because plants don't change location, the plant fixed effects nest state fixed effects. I also run the following alternative specification that allows for heterogeneous variation in outcomes by generator ownership status,

$$\begin{aligned} Y_{isjt} = &\beta^N \, 1(\text{Gen}_{it} = 0) \times \text{Shortage}_{st} + \beta^G \, 1(\text{Gen}_{it} = 1) \times \text{Shortage}_{st} \\ &+ \gamma X_{isjt} + \theta S_{st} + \nu_i + \lambda_{jt} + \varepsilon_{isjt}, \end{aligned} \tag{4.2}$$

where $1(\text{Generator} = 0)$ ($1(\text{Generator} = 1)$) is an indicator for whether the plant doesn't own (owns) a generator in period t. The regression from equation (4.2) is equivalent to residualizing the outcome variable by regressing it on all covariates except "Shortage," then regressing the residualized outcome on "Shortage" separately for plants with and without generators. Notably, I am able to include plant fixed-effects in this specification because generator ownership varies at the plant level. Therefore, the coefficients on the generator ownership interacted with shortage should be interpreted as within-plant differences.

Table 4.1 reports the results of the aforementioned regressions for three outcomes: the (logged) quantity of grid electricity consumed, the (logged) quantity of electricity self-generated, and the self-generated electricity as a share of total electricity consumption (which is zero for plants without generators). The estimated coefficients show that grid electricity consumption is negatively correlated with the shortage measure, whereas self-generation, both in quantity (which conditions on positive self-generation) and share, is positively so. All coefficients are statistically significant at 99% and the signs are robust to the inclusion of state-specific linear time trends (see Table C.1). Furthermore, the estimates of β^N and β^G from specification (4.2) are almost identical in magnitude and not significantly different, implying that grid electricity consumption is similarly correlated with shortages independent of whether the plant owns a generator in that period.

As an additional robustness check, I run the same specifications using log(Availability) as the regressor instead of shortage. As "Availability" is the CEA's measure of quantity supplied, it is likely less subject to measurement error than the shortage variable that includes the CEA's measure of quantity demanded. Table C.2 reports the results from these specifications, which are consistent with the patterns from Table 4.1.

Altogether, the regression analysis of electricity usage by ASI plants strongly suggests the CEA's state-level shortage measure is indeed an informative measure of electricity shortages by plants.

Table 4.1: Grid electricity and self-generation variation with the Shortage variable

	(1) log(Grid Elec.)	(2) log(Grid Elec.)	(3) log(Gen. Elec.)	(4) Gen. Share
Shortage	-0.578***		3.760***	0.120***
	(0.0941)		(0.384)	(0.0249)
1(Gen. = 0) × Shortage		-0.577***		
		(0.0970)		
1(Gen. = 1) × Shortage		-0.580***		
		(0.104)		
Observations	333,057	333,057	116,275	333,057
R-squared	0.946	0.946	0.838	0.647
Plant FE	Yes	Yes	Yes	Yes
NIC4 x Year FE	Yes	Yes	Yes	Yes

Dependent variable in specifications (1) and (2) is grid electricity onsumption (logged). In specifications (3) and (4), the dependent variable is (log-) electricity generated and the generated electricity share of total electricity consumption. Cluster-robust standard errors, adjusted for two-way clustering on plant and state-year. *** p<0.01, ** p<0.05, * p<0.1.

4.3.2 Investment and Electricity Shortages

To study the response of investment to electricity shortages, I use the following specification given in equation (4.3):

$$\begin{aligned} Y_{isjt} = {} & \underbrace{\beta^N 1(\text{Gen}_{it} = 0) \times \text{Shortage}_{st} + \beta^G 1(\text{Gen}_{it} = 1) \times \text{Shortage}_{st}}_{\text{Investment-Shortage Relationship by Generator Type}} \\ & + \underbrace{\delta^C 1(\text{Gen}_{it} = 1 | \text{Gen}_{i,t-1} = 1)}_{\text{Generator Continuation}} + \underbrace{\delta^A 1(\text{Gen}_{it} = 1 | \text{Gen}_{i,t-1} = 1)}_{\text{Generator Adoption}} \\ & + \underbrace{\delta^R 1(\text{Gen}_{it} = 0 | \text{Gen}_{i,t-1} = 1)}_{\text{Generator Removal}} + \gamma X_{isjt} + \theta S_{st} + \nu_i + \lambda_{jt} + \varepsilon_{isjt} \end{aligned} \tag{4.3}$$

This specification is intended to capture heterogeneous investment correlations with electricity shortages through the coefficients β^N for non-generating plants and β^G for self-generating plants. Furthermore, it also allows for a direct relationship between generator ownership and the outcome variable, conditional on the shortage level. Specifically, I include dummies for continued generator ownership ($1(\text{Gen}_{it} = 1|\text{Gen}_{i,t-1} = 1)$), generator adoption ($1(\text{Gen}_{it} = 1|\text{Gen}_{i,t-1} = 1)$) and generator removal ($1(\text{Gen}_{it} = 0|\text{Gen}_{i,t-1} = 1)$).[5] Although a dummy for self-generation could be used instead (the coefficient on which would be a weighted average of δ^C, δ^A and δ^R), I estimate coefficients for the three types of generator transitions separately to allow for potential discontinuous changes to the returns on investment when plants either adopt or remove generators. Additionally, because I don't observe a generator capital stock or investment, adoption and removal events could contaminate the reported investment measure by directly entering investment expenditures. For these two reasons, I view the coefficient δ^C as best capturing the relationship between generator ownership and investment in productive capital.

My preferred measure of investment is the investment rate - defined as investment expenditures during the year as a fraction of the capital stock at the beginning of the year - as it includes observations of zero or negative investment, of which both are present in the data. I also report results for logged investment expenditures as an outcome, which conditions on plants reporting positive investment. As investment expenditures might suffer contamination from expenditures on generators as described previously, I also include logged investment expenditures in non-equipment capital, defined as total investment expenditures less the investment expenditures on equipment capital. Since generators should be categorized as equipment capital, this measure of investment most likely excludes any generator-related investment expenses.[6] The regression results of specification (4.3) with these three outcomes are reported in Table 4.2.

Notably, negative estimates of β^N and β^G for all three outcome variables imply that, on average, plants invest less when electricity shortages are high. Although not strictly causal

5. I use this notation for convenience. All transitions are defined using the last observed period for each plant.

6. "Non-equipment capital" includes land and structures along with transport, computer, and pollution-control equipment as these categories are separately reported in the ASI. I use "equipment capital" to refer to the capital stock reported under the "Plant and Machinery;" generator capital is likely to fall into this category. The mean (median) share of non-equipment capital is 52% (43%) among those plants that report owning capital in any of the aforementioned categories.

Table 4.2: Investment Relationship with Shortages and Generators

	(1)	(2)	(3)
	I/K	$\log(I)$	$\log(I_{neq})$
$1(\text{Gen.} = 0) \times$ Shortage	-0.166***	-0.693***	-0.559**
	(0.0523)	(0.197)	(0.240)
$1(\text{Gen.} = 1) \times$ Shortage	-0.0995*	-0.271	-0.109
	(0.0597)	(0.206)	(0.264)
$1(\text{Gen}_{it} = 1 \mid \text{Gen}_{i,t-1} = 1)$	-0.0283***	-0.0358*	-0.0461*
	(0.00543)	(0.0190)	(0.0246)
$1(\text{Gen}_{it} = 1 \mid \text{Gen}_{i,t-1} = 0)$	-0.00913	0.0315	-0.0161
	(0.00708)	(0.0232)	(0.0287)
$1(\text{Gen}_{it} = 0 \mid \text{Gen}_{i,t-1} = 1)$	0.0122**	0.0402**	0.0165
	(0.00601)	(0.0198)	(0.0265)
Observations	325,611	244,828	160,906
R-squared	0.419	0.744	0.702
Plant FE	Yes	Yes	Yes
NIC4 x Year FE	Yes	Yes	Yes

Dependent variables in specifications (1), (2) and (3) are the investment rate, log of investment expenditures and log of investment expenditures on non-equipment capital. Standard errors adjusted for two-way clustering on plant and state-year. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. $p-$values from Wald tests of $\beta^N = \beta^G$: 0.235, 0.0255 and 0.0694 for columns (1), (2) and (3) respectively.

estimates due to the potential endogeneity of shortages, these estimates provide support for electricity shortages reducing investment. Consider the potential sources of endogeneity: First, large investment by plants may lead to an increase in electricity demand and therefore an increase in shortages. Simultaneity of this form would bias estimates of β^N and β^G upwards, and hence suggest the estimates from Table 4.2 are, in fact, conservative. On the other hand, states with higher shortages may also be less financially developed or have weaker institutions, both of which could adversely affect investment. To the extent that they are permanent, such institutional features are accounted for by the plant fixed effects. I also include a proxy for financial development in the number of bank branches in the state to condition on potential state-year variation. Finally, Allcott et al. (2016) find a causal negative effect of the CEA shortage variable on plant revenues, which provides a direct channel for electricity shortages reducing the rate of return on capital.

Additionally, estimates of β^N are lower than β^G across all specification, implying that shortages reduce investment less for plants with generators. This result is intuitive since plants use generators precisely to insure against electricity shortages. This difference is stark and statistically significant (at 5% and 10%, respectively) for logged total and non-equipment investment expenditures. Lastly, as capital is dynamic and investment decisions are based on plants' expectations of the future, a negative relationship with contemporaneous shortages suggests that plants use realized shortages to forecast future shortages.

The coefficients δ^C, δ^A, and δ^R are informative of the joint dynamics of investment in productive capital and generators. Due to the aforementioned discontinuities in the returns to investment during adoption and removal spells, I view the coefficient δ^C as particularly informative about any potential crowding out of productive capital by generators. In particular, negative estimates of δ^C imply that, conditional on the shortage level, plants invest less on average when they are continuing self-generators than when they are continuing non-generators. The magnitude of δ^C implies that, conditional on the shortage level, plants invest 2.83% less on average during spells of continuing self-generation. Going further, these results suggest that plants face lower returns to investment during periods of self-generation. In turn, this finding then implies that self-generation capabilities are costly and potentially disruptive, making plants less profitable than they would be without generators. Reinikka and Svensson (2002) use a similar specification on a sample of Ugandan firms, and their findings also support the crowding-out effect of generators on investment, though they cannot include plant fixed effects or distinguish between adoption, removal, and continuation due to the cross-sectional nature of their study.

Though not as strongly informative as the estimates for δ^C, the estimates of δ^A and δ^R are still consistent with the generator crowd-out effect. Positive estimates of δ^R imply plants invest more upon removing their existing generator, suggesting that this removal leads to high returns on investment. δ^A is the hardest to interpret as generator adoption could mechanically increase investment expenditures; however, investment in non-equipment capital is free of such confounding. While not statistically significant, a negative estimate of δ^A (column 3 of Table 4.2) suggests that, despite being insured against future electricity shortages (and having a greater incentive to invest), costs associated with generator ownership are high enough for the net effect on investment to be negative. These results are also robust to the inclusion of state-specific time trends as well as alternative controls for financial development (Tables C.3 and C.4).

Taken together, these results highlight the importance of studying the joint dynamics of investment and generator adoption in conjunction with electricity shortages. Evaluating the full impact of electricity shortages requires accounting for not only the direct effect, but also the indirect impact of generator ownership (which is driven by electricity shortages) on investment.

4.3.3 Mechanisms

To inform the model, I test two potential channels through which electricity shortages can reduce investment. The first is through reduced capital utilization: Since capital is fixed in the short-run, electricity shortages (realized as power outages) could interrupt production, leading to foregone output and reduced capacity utilization. While I observe the latter directly, my preferred measure of utilization is man-days per worker as it is more likely to capture partial capacity utilization than the working days measures. In particular, suppose a plant experiences is a two-hour power outage during a particular day and operates for eight hours instead of ten. It is likely that day would still be reported as a working day, despite the realization of a power outage. Hence, the working day measure is likely to understate small changes in utilization. Man-days per worker suffers less from this problem; a plant may shut down certain activities during days with power outages and utilize only part of its workforce, which would be reflected in this measure.

Table 4.3 reports the results of a regression of the various capacity-utilization measures on shortage using the specification from (4.2). Together, they suggest electricity shortages are indeed correlated with lower capacity utilization. Furthermore, the change in man-days per worker is larger than the change in working days, reinforcing the idea that the latter is a coarser measure. The estimated coefficient for plants without generators implies a 10 p.p. increase in shortage is associated with a 0.6% decrease in man-days per worker. The same direction is implied by the coefficients on the other utilization measures for non-generators. The coefficient for the interaction term with generators is larger than that for without, intuitively suggesting plants have higher capital utilization during spells of generator ownership. Lastly, though not explicitly included as a mechanism in this study, the coefficients from (3) and (4) suggest some potential reorganizing of production schedules due to electricity shortages.[7]

Although I find motivating evidence for reduced utilization as a mechanism, anecdotes suggest manufacturers worry about their equipment being damaged due to unexpected power outages. Though not directly observable in the data, such damage would potentially appear

7. The number of missing values for non-manufacturing days is very high, so the results from column (4) should be interpreted with caution.

Table 4.3: Capacity Utilization and Shortages

	(1)	(2)	(3)	(4)
1(Gen. = 0) × Shortage	-0.0647***	-0.0383**	-0.0198	-1.760***
	(0.0165)	(0.0191)	(0.0191)	(0.390)
1(Gen. = 1) × Shortage	0.00163	0.0235	0.0442**	-1.663***
	(0.0160)	(0.0192)	(0.0185)	(0.386)
Observations	326,580	299,254	300,275	29,117
R-squared	0.754	0.697	0.731	0.831
Plant FE	Yes	Yes	Yes	Yes
NIC4 x Year FE	Yes	Yes	Yes	Yes

Dependent variables by column are as follows: (1) log(Man-days per worker), (2) log(working days), (3) log(manufacturing days) and (4) log(non-manufacturing days). Omitted controls include log(GSDP per capita), log(Population), log(Age) and log(Electricity Price). Standard errors adjusted for two-way clustering on plant and state-year. *** p<0.01, ** p<0.05, * p<0.1.

in the depreciation costs reported by plants. To test this depreciation channel, I regress the depreciation rate using the same specification and find that electricity shortages are correlated with a reduction in the depreciation rate reported by plants (see Table C.5). This runs counter to the posited direction and is in fact consistent with a model of utilization-dependent depreciation; lower utilization due to electricity shortages should also result in lower depreciation. The implied magnitudes, however, are small and likely unimportant quantitatively. Therefore, I exclude the potential impacts of shortages on depreciation from the rest of my analysis.

CHAPTER 5

A MODEL OF INVESTMENT DYNAMICS AND GENERATOR ADOPTION

To rationalize the patterns from chapter 4 as well as to quantify the effects of electricity shortages on plants, I develop a dynamic model of investment augmented with shortage shocks and generator adoption. In its most general form, the model is described recursively by

$$V^N(K_{it}, \Theta_{it}) =$$
$$\max \begin{cases} \max\limits_{I_{it}} \Pi^N(K_{it}, \Theta_{it}) - C_K(I_{it}, K_{it}, \Theta_{it}) + \rho\mathbb{E}[V^N(K_{i,t+1}, \Theta_{i,t+1})|\Theta_{it}] \\ \max\limits_{I_{it}} \Pi^N(K_{it}, \Theta_{it}) - C_K(I_{it}, K_{it}, \Theta_{it}) - C_G^A(K_{it}, \Theta_{it}) + \rho\mathbb{E}[V^G(K_{i,t+1}, \Theta_{i,t+1})|\Theta_{it}] \end{cases} \tag{5.1}$$

$$V^G(K_{it}, \Theta_{it}) =$$
$$\max \begin{cases} \max\limits_{I_{it}} \Pi^G(K_{it}, \Theta_{it}) - C_K(I_{it}, K_{it}, \Theta_{it}) - C_G^M(K_{it}, \Theta_{it}) + \rho\mathbb{E}[V^N(K_{i,t+1}, \Theta_{i,t+1})|\Theta_{it}] \\ \max\limits_{I_{it}} \Pi^G(K_{it}, \Theta_{it}) - C_K(I_{it}, K_{it}, \Theta_{it}) - C_G^M(K_{it}, \Theta_{it}) + \rho\mathbb{E}[V^G(K_{i,t+1}, \Theta_{i,t+1})|\Theta_{it}] \end{cases} \tag{5.2}$$

s.t.

$$K_{i,t+1} = (1 - \delta)K_{it} + I_{it} \tag{5.3}$$

$$\Theta_{i,t+1} = G(\Theta_{it}, \xi_{i,t+1}), \tag{5.4}$$

where K_{it} is the plant's capital stock, $\{N, G\}$ is a binary state that denotes the plant's generator ownership status, and Θ_{it} is a vector of exogenous states that follows a general first-order Markov process. $\Pi^N(\cdot)$ and $\Pi^G(\cdot)$ are the contemporaneous variable profits of plants without and with generators, respectively.

Plants' decision processes are as follows. From equation 5.1, in each period, plants without generators simultaneously choose their investment level in productive capital and whether to adopt a generator in the next period. Plants that choose to adopt pay a sunk adoption cost denoted by $C_G^A(\cdot)$. Similarly, plants with generators (equation 5.2) choose, along with their investment level, whether to continue owning a generator for the next period. While removing a generator is not costly, plants that have generators face a recurring "maintenance" cost of $C_G^M(\cdot)$. Plants face a cost of adjusting their capital stock denoted by $C_K(\cdot)$. In addition, the model implicitly assumes a one-period-to-build constraint for both productive capital and generators, implying that plants cannot contemporaneously adjust their capital stock or generator status in response to the exogenous state.

In the rest of this chapter, I proceed to describe the parametrization of this general model.

5.1 Exogenous States

To capture the state dependence of the returns to both types of dynamic decisions, the exogenous state consists of a plant-level productivity shock A_{it} as well as an aggregate electricity shortage shock B_t. I assume that (log-)productivity follows an AR(1) process given by

$$\log(A_{i,t+1}) = (1-\rho_A)\mu_A + \rho_A \log(A_{it}) + \varepsilon^A_{i,t+1}, \quad \varepsilon^A_{it} \overset{\text{i.i.d.}}{\sim} N(0, \sigma^2_A) \tag{5.5}$$

Electricity shortages reflect positive excess demand in electricity markets, and are therefore bounded below by zero. Let B_t^* denote the aggregate excess demand, in which case the market shortage is given by $B_t = \max\{B_t^*, 0\}$. As B_t^* only reflects differences between quantity demanded and supplied, I don't bound it and assume it also follows an AR(1) process given by

$$B^*_{t+1} = (1-\rho_B)\mu_B + \rho_B B^*_t + \varepsilon^B_{t+1}, \ \ \varepsilon^B_{t+1} \overset{\text{i.i.d}}{\sim} N(0, \sigma^2_B)$$

The shortage process specification merits discussion. Since I assume that electricity shortages are exogenously determined, the model rules out endogenous responses by electricity suppliers/policymakers as well as general equilibrium effects. Second, the relatively simple AR(1) specification assumes that past shortage levels adequately capture all the relevant information on the supply side of electricity markets. Such an assumption is reasonable given the evidence from chapter 4; at the very least, plants appear to forecast future shortages using contemporaneous shortages. An additional benefit of the AR(1) specification is the relatively clear economic interpretation of the parameters: The parameter μ_B reflects the long-run average shortage level or scarcity while σ_B speaks to the uncertainty or reliability of electricity supply. Furthermore, Since the distortions underlying the shortage shocks vary widely geographically and intertemporally, this relatively parsimonious specification makes the model generalizable, allowing for comparisons across different states and policy regimes.[1]

The independence assumption between the two shocks is potentially a strong one. In particular, if sectoral productivity shocks to manufacturing shift the aggregate demand for electricity, shortage shocks could be correlated with the aggregate productivity shock. Furthermore, introducing aggregate productivity shocks and allowing them to be correlated with the market-level shortage shocks could also approximate general equilibrium effects without explicitly modeling them. In future iterations of this work, I plan to relax the assumption of independence between productivity and shortages.

1. With an eye toward estimation, this specification also allows for the model to be solved in a computationally tractable manner.

5.2 Static Production and Variable Profits

An underlying model of production is useful in mapping investment behavior from the general dynamic model to outcomes of interest such as value added and input demand, though one isn't required in principle.[2] Furthermore, a model of production helps microfound parametrizations of the profit functions in the dynamic model.

Because they find a strong quantitative agreement for their estimated short-run effects with their model using similar data, the static setup I choose closely follows that of Allcott et al. (2016). For the sake of exposition, I refer to a period as a month.

Each month t consists of a measure 1 of days, with days indexed by τ. I assume a decreasing returns to scale, Cobb-Douglas production technology in four inputs - capital, labor, materials, and electricity. A benefit of using a Cobb-Douglas specification is that it yields closed form profit functions. The problem of plant i in month t is given.

$$Q_{it\tau} = A_{it\tau}^{\eta} \left(K_{it\tau}^{\alpha_k} L_{it\tau}^{\alpha_l} M_{it\tau}^{\alpha_m} E_{it\tau}^{\alpha_e} \right)^{1-\eta}. \tag{5.6}$$

$Q_{it\tau}$ represents the physical output on day τ, and $X_{it\tau}$ represents the quantity of input X used on day τ. $A_{it\tau}$ is plant i's total factor productivity. The parameters $\alpha_k + \alpha_l + \alpha_m + \alpha_e = 1$, and the parameter $\eta \in (0,1)$ determines the decreasing returns to scale. I assume that plant i faces perfectly elastic demand at a price p, normalized to 1. Therefore, i's monthly revenue is given by

$$Y_{it} = \int_0^1 A_{it\tau}^{\eta} \left(K_{it\tau}^{\alpha_k} L_{it\tau}^{\alpha_l} M_{it\tau}^{\alpha_m} E_{it\tau}^{\alpha_e} \right)^{1-\eta} d\tau. \tag{5.7}$$

Allcott et al. (2016) interpret the shortage variable as utilization shocks, and since I find evidence consistent with the same mechanism, I adopt their interpretation. Plants

2. Alternatively, the profit functions could be directly estimated with productivity shocks replaced by profitability shocks as in Cooper and Haltiwanger (2006). However, such a model would not be able to speak to output outcomes.

experiencing a shortage shock of B_t are unable to produce for a measure B_t of the month unless they own a generator. The decreasing returns to scale assumption ensures that plants always earn positive profits.[3] Under these assumptions, revenue- and quantity-TFP are equal, though the TFP shocks should be interpreted as revenue-TFP shocks.[4]

Before proceeding with the plant i's static optimization problem, the timing of its decisions are as follows:

1. TFP and capital stock are fixed for the month, that is, $A_{it\tau} = A_{it}$ and $K_{it\tau} = K_{it}$.
2. Given A_{it} and K_{it}, plant i observes the electricity shortage state $B_t \in [0, 1]$, realized as a fraction of the month for which grid electricity is unavailable.
3. The firm chooses its labor inputs L_{it} after observing B_t, but cannot adjust it day to day.
4. Materials $M_{it\tau}$ and energy $E_{it\tau}$ are chosen daily, subject to shortage utilization constraints.

Finally, let $\beta_x = \alpha_x(1 - \eta)$ denote the revenue elasticity of input $x \in \{K, L, M, E\}$.

5.2.1 Plants without Generators.

Plants without generators cannot produce for a fraction B_t of the month because $E_{i\tau t}$ is forced to 0 in that measure. Therefore, plant i's profit maximization problem is

$$\max_{L_{it}, M_{it\tau}, E_{it\tau}} A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} \int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e} d\tau - w_t L_{it} - p_t^m \int_0^{1-B_t} M_{it\tau} d\tau - p_t^e \int_0^{1-B_t} E_{it\tau} d\tau. \tag{5.8}$$

3. An assumption that would result in a similar parametrization of revenues would be that plants face isoelastic demand curves with an elasticity of demand of $1/\eta$.

4. See Foster et al. (2008) for a discussion of quantity-TFP and revenue-TFP measures. Haltiwanger et al. (2018) also point out potential sources of differences between TFPQ and TFPR, particularly due to demand shifts.

The first-order conditions are given by

$$
\begin{aligned}
[L_{it}]:\ & \beta_l A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l-1} \int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e} - w_t = 0 \\
[M_{it\tau}]:\ & \beta_m A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it\tau}^{\beta_m-1} E_{it\tau}^{\beta_e} - p_t^m = 0 \\
[E_{it\tau}]:\ & \beta_e A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e-1} - p_t^e = 0.
\end{aligned}
$$

In the absence of shortages (equivalently when $B_t = 0$), the plant's problem reduces to a static Cobb-Douglas profit maximization problem that yields the profit function given by

$$\pi(K_{it}, A_{it}) = \kappa(w_t, p_t^m, p_t^e) A_{it}^{\eta/(\beta_k+\eta)} K_{it}^{\beta_k/(\beta_k+\eta)}, \tag{5.9}$$

where

$$\kappa(w_t, p_t^m, p_t^e) = (\beta_k + \eta) \left[\left(\frac{\beta_l}{w_t}\right)^{\beta_l} \left(\frac{\beta_m}{p_t^m}\right)^{\beta_m} \left(\frac{\beta_e}{p_t^e}\right)^{\beta_e} \right]^{1/(\beta_k+\eta)}. \tag{5.10}$$

$\pi(\cdot)$ is a useful quantity to define and should be interpreted as plant profits in the absence of shortages. For convenience in exposition, I refer to $\pi(\cdot)$ as the profitability.

For $B_t \geq 0$, the resulting profit function, conditional on capital, productivity, and shortages, is given by

$$\Pi^N(K_{it}, A_{it}, B_t) = (1 - B_t)^{(\beta_l+\beta_k+\eta)/(\beta_k+\eta)} \pi(K_{it}, A_{it}) \tag{5.11}$$

From (5.11), shortages can be interpreted as non-linear profit taxes. The non-linearity arises from the fact that plants cannot perfectly adjust all inputs (specifically labor and capital) in response to shortage states.

5.2.2 Plants with Generators.

Plants with generators can produce during shortage days, but pay a higher unit cost for electricity $p_t^g > p_t^e$. Letting $M_{iGt\tau}$ and $E_{iGt\tau}$ denote a self-generating plant's material and energy input choices on blackout days, its profit-maximization problem is

$$\begin{aligned} \max_{L_{it}, M_{it\tau}, E_{it\tau}, M_{iGt\tau}, E_{iGt\tau}} & A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} \left(\int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e} d\tau + \int_0^{B_t} M_{iGt\tau}^{\beta_m} E_{iGt\tau}^{\beta_e} d\tau \right) - w_t L_{it} \\ & - p_t^m \left(\int_0^{1-B_t} M_{it\tau} d\tau + \int_0^{B_t} M_{iGt\tau} d\tau \right) \\ & - p_t^e \int_0^{1-B_t} E_{it\tau} d\tau - p_t^g \int_0^{B_t} E_{iGt\tau} d\tau. \end{aligned} \tag{5.12}$$

Note that because the production function has decreasing returns to scale, plants with generators will find it optimal to produce during all shortage days as they earn positive profits from producing on any scale. The first-order conditions are given by

$$\begin{aligned} [L_{it}]:\ & \beta_l A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l - 1} \left(\int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e} d\tau + \int_0^{B_t} M_{iGt\tau}^{\beta_m} E_{iGt\tau}^{\beta_e} d\tau \right) - w_t = 0 \\ [M_{it\tau}]:\ & \beta_m A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it\tau}^{\beta_m - 1} E_{it\tau}^{\beta_e} - p_t^m = 0 \\ [E_{it\tau}]:\ & \beta_e A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e - 1} - p_t^e = 0 \\ [M_{iGt\tau}]:\ & \beta_m A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{iGt\tau}^{\beta_m - 1} E_{iGt\tau}^{\beta_e} - p_t^m = 0 \\ [E_{iGt\tau}]:\ & \beta_e A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{iGt\tau}^{\beta_m} E_{iGt\tau}^{\beta_e - 1} - p_t^g = 0. \end{aligned}$$

Solving for optimal input choices yields the following profit function for plants with generators:

$$\Pi^G(K_{it}, A_{it}, B_t) = \left(1 - B_t + B_t \left(\frac{p_t^e}{p_t^g} \right)^{\beta_e/(\beta_l+\beta_k+\eta)} \right)^{(\beta_l+\beta_k+\eta)/(\beta_k+\eta)} \pi(K_{it}, A_{it}) \tag{5.13}$$

where $\pi(K_{it}, A_{it})$ is defined as before.

As seen from equation (5.13), plants with generators can (imperfectly) mitigate the profit tax effect of blackouts. Two points are worth noting here. First, the ability of a self-generating firm to mitigate the effect of shortages is intuitively decreasing as the price of self-generated electricity increases relative to the price of grid electricity; if the price of self-generated electricity is equal to that of grid electricity, then plants with generators are able to perfectly mitigate the effect of shortages. Second, the ability to mitigate the effect of shortages is decreasing in the importance of electricity as an input (i.e., when β_e is higher); a higher revenue elasticity for electricity implies that reduced electricity consumption during blackout days (due to the higher price of self-generated electricity) reduces output on shortage days by more, relative to output on non-shortage days.

5.3 Capital Adjustment Costs

Motivated by the similar investment patterns in the ASI data, I closely follow the investment dynamics literature and assume the presence of both non-convex and convex adjustment costs to capital. Specifically,

$$C_K(I_{it}, K_{it}, \Theta_{it}) = \Pi^X(K_{it}, A_{it}) \cdot C_K^F \cdot 1\{I_{it} \neq 0\} + I_{it} + \frac{C_K^Q}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it} \tag{5.14}$$

for $X \in \{N, G\}$. The presence of quadratic adjustment costs dampens the response of investment to productivity or electricity shortage shocks. The fixed cost of investment leads to economies of scale in investment, generating inaction as well as large bursts of investment.

Various specifications of the fixed cost have been used in the investment dynamics literature. The specification in equation (5.14) was introduced by Caballero and Engel (1999) and Cooper et al. (1999); Cooper and Haltiwanger (2006) refer to this specification as the "opportunity cost" specification of adjustment costs, capturing the disruptive nature of investment on productive activities. This specification is also used by Asker et al. (2014) and Johnston (2018).

I also estimate the model using an alternative specification commonly used in the literature (e.g. Bloom, 2009; Cooper and Haltiwanger, 2006, also test the following "fixed cost" specification, though they find the previous specification fits the U.S. data better).

$$C_K(I_{it}, K_{it}, \Theta_{it}) = K_{it} \cdot C_K^F \cdot 1\{I_{it} \neq 0\} + I_{it} + \frac{C_K^Q}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it} \tag{5.15}$$

Notably, both specifications imply plants never exit - small enough plants will always find it optimal to invest, preventing their capital stock from depreciating fully in the limit.

5.4 Generator Costs

I parametrize the generator adoption and maintenance costs to include both fixed and variable components as follows

$$C_G^A(K_{it}, A_{it}, B_t) = C_G^{A,F} + C_G^{A,V}\pi(K_{it}, A_{it}) \tag{5.16}$$

$$C_G^M(K_{it}, A_{it}, B_t) = C_G^{M,F} + C_G^{M,V}\pi(K_{it}, A_{it}), \tag{5.17}$$

where $C_G^{A,F}$ and $C_G^{M,F}$ are fixed, size-invariant costs and $C_G^{A,V}$ and $C_G^{M,V}$ represent variable costs that are proportional to the profitability of plants. The fixed components allow for economies of scale in generator adoption and ownership, whereas the variable components act as drags on the profitability of plants, allowing for generators to affect the returns to investment in productive capital. The parametrization of the variable costs is rationalized by the fact that daily energy demand (a proxy for required generator capacity) is proportional to the profitability of plants.

Although generator prices are certainly a component of these costs, $C_G^A(\cdot)$ and $C_G^M(\cdot)$ should be interpreted more broadly. The adoption cost is a sunk cost that could reflect search frictions in the market for generators, or sunk costs of delivery and installation. Similarly, the maintenance cost $C_G^M(\cdot)$ not only reflects the literal costs of physically maintaining a generator, but can be broadly interpreted as the opportunity cost of owning a generator in that generators require resources that could otherwise be used productively. The components of this cost could include floor space allocated for the generator, costs of fuel acquisition and storage, and actual maintenance costs for physical wear and tear of the generator.

A non-zero variable maintenance cost parameter allows for generator ownership to crowd out investment in productive capital. The intuition is that the larger a plant gets, the more resources are required to maintain self-generating capabilities, potentially reducing the incentive to invest. The net investment effect of generator adoption then depends on the ability of generators to mitigate losses due to shortages (more investment) and the size of $C_G^{M,V}$ (less investment), and is therefore ambiguous.

Lastly, I assume that the maintenance cost does not depend on the utilization of generators (i.e., on the shortage level). This assumption is akin to that of fixed depreciation for general capital goods. Though a utilization cost could be included in the specification to without qualitatively changing the model's predictions, such a cost cannot be identified given the current data.

5.5 Solving the Dynamic Model: An Illustrative Example

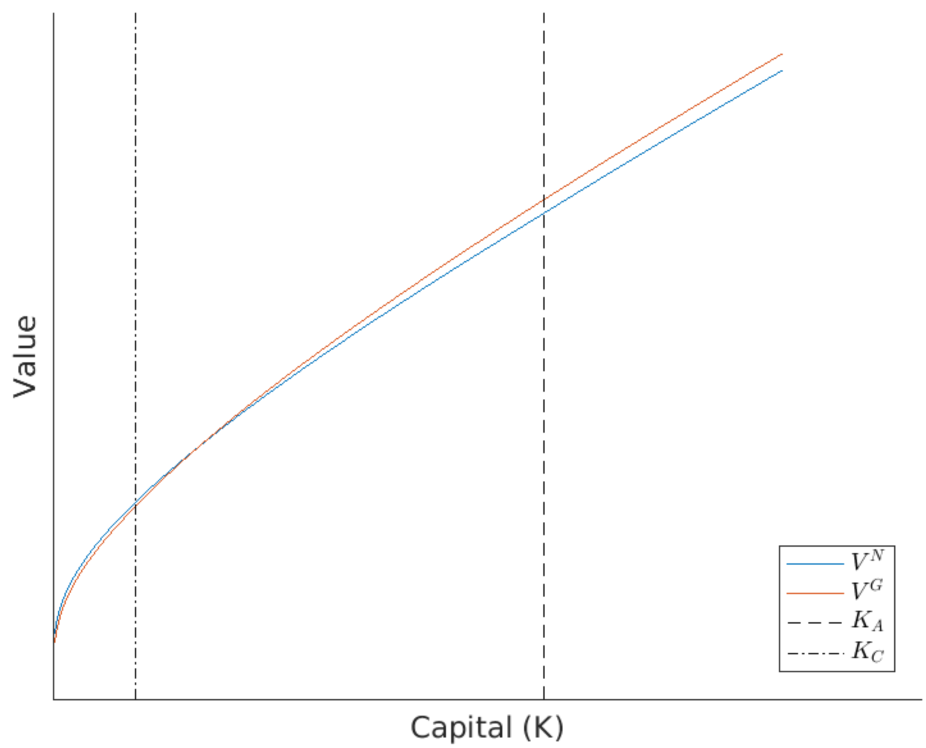
The solution to the dynamic model requires solving for the value functions $V^N(K_{it}, \Theta_{it})$ and $V^G(K_{it}, \Theta_{it})$ along with policy functions, which are doubles $(H^N(K_{it}, \Theta_{it}), g^N(K_{it}, \Theta_{it}))$ and $(H^G(K_{it}, \Theta_{it}), g^G(K_{it}, \Theta_{it}))$, where $H^N(\cdot)$ and $H^G(\cdot)$ are investment decisions while $g^N(\cdot)$ and $g^G(\cdot)$ are generator adoption/continuation decisions for plants without and with generators respectively.

The model does not yield closed-form solutions for the value and policy functions, so I discretize the state-space and solve the model numerically. Going forward in this chapter, I provide a simulated illustrative example of how generator adoption and investment interact in the model. The goal of this example is to examine heterogeneous investment responses by plants depending on their size and self-generating status, particularly to shed light on how the model can generate the investment distributions by generator type in Figure 4.4. However, this example is not representative of the set of solutions to the model and does depend on the value of the parameters. In particular, I focus on a case that generates partial generator ownership.

Figure 5.1 plots the value functions V^N and V^G holding the exogenous state (A, B) constant. Although the slope of V^G is more positive than the slope of V^N, the presence of fixed costs in the generator maintenance cost shift the intercept on V^G below that of V^N, leading to a single crossing point for the two value functions above which the value of a plant with a generator is higher than the value for a plant without. Intuitively, this single-crossing feature should suggest a cutoff rule for generator adoption at the crossing point. However, because sunk adoption costs create partial irreversibility in generator adoption, non-generating plants choose to delay adoption. This delay is seen from the adoption cutoff K_A being to the right of the single crossing point; non-generating plants with a capital stock greater than K_A will choose to adopt a generator. Similarly, plants with generators will choose to delay removal, leading to a shifting of the continuation cutoff K_C to the left of the crossing point, where generating plants with size above K_C will choose to continue with a generator in the next period. The region between K_C and K_A is where differences should arise in the investment behavior for plants, depending on whether they self-generate.

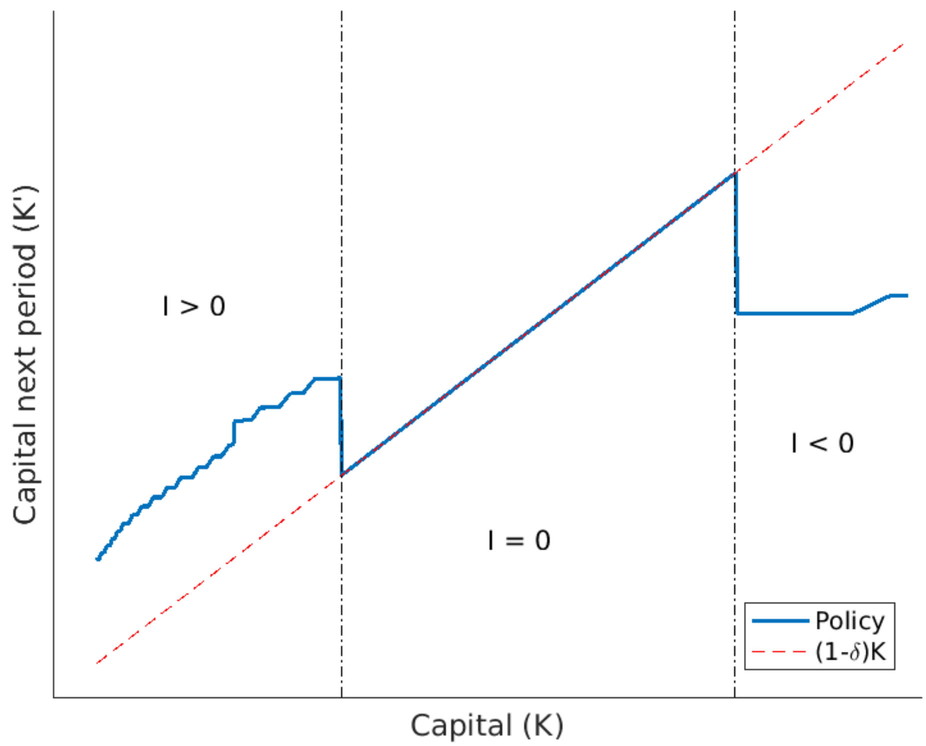
Before examining the policy functions, Figure 5.2 plots the typical investment policy function in models of investment with both fixed and quadratic adjustment costs (ignoring shortages). Conditional on productivity, the typical policy rule consists of cutoffs that divide the capital state-space into three regions: a region of positive investment for smaller plants, a region of inaction for larger plants that are unwilling to incur the fixed cost to adjust their capital stock, and a region of negative investment for very large plants. Going forward, the simulated example with shortages focuses on when generator adoption occurs in the region of positive investment to show how the two investment margins interact.

Figure 5.1: Example Value Functions



Plots the value functions V^N and V^G holding the exogenous state (A, B) constant. K_A and K_C are the adoption and continuation cutoffs for plants without and with generators, respectively.

Figure 5.2: Typical Policy Function in Models of Investment with Non-convex and Convex Adjustment Costs

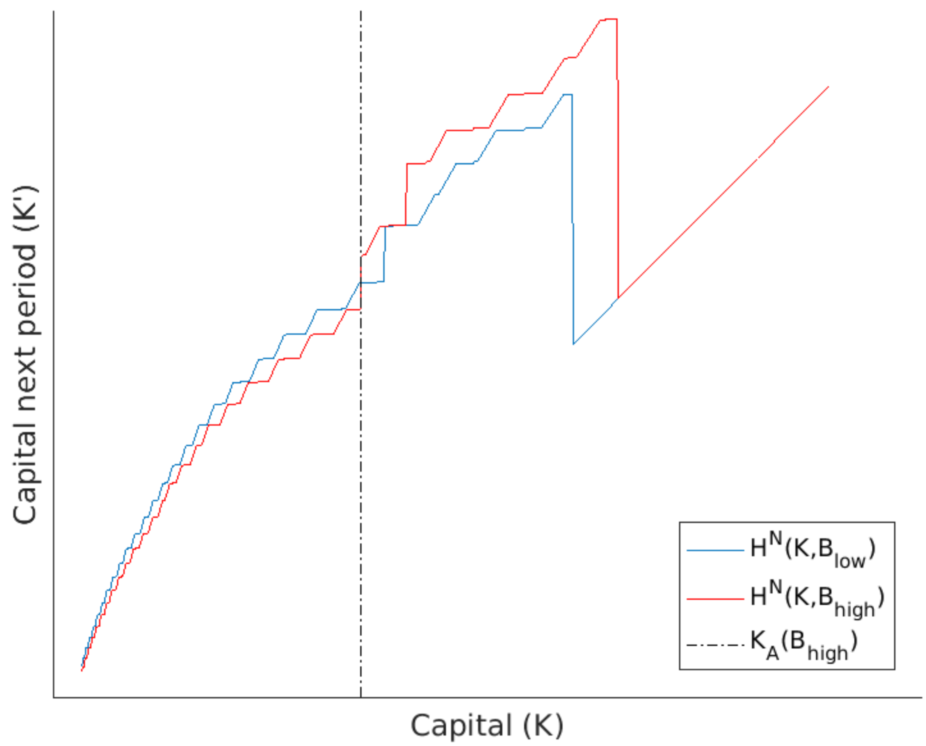


Plots the policy function for a plant conditional on productivity in a model with both fixed and quadratic adjustment costs (described in Equation 5.15).

Figure 5.3 plots the investment policy as a function of present capital stock for plants without generators under a lower (better) shortage state B_{low} and a higher (worse) shortage state B_{high} holding productivity fixed. Generator adoption is not optimal under B_{low} for any plants while $K_A(B_{high})$ is the adoption cutoff for plants in the high shortage state. Due to economies of scale in generator ownership, plants respond heterogeneously in the high shortage state depending on their size (defined by their capital stock). Compared to the investment policy under the low shortage state, smaller plants invest less in capital and don't adopt generators. On the other hand, larger plants choose to adopt generators and invest more than they would have in the lower shortage state, as is seen by the spike in investment at the adoption threshold K_A. Hence, according to the model, the generator margin can generate potential non-monotonicities in the investment response to electricity shortages. Furthermore, generator adoption can distort the plant-size distribution by differentially affecting the returns to investment for large plants.

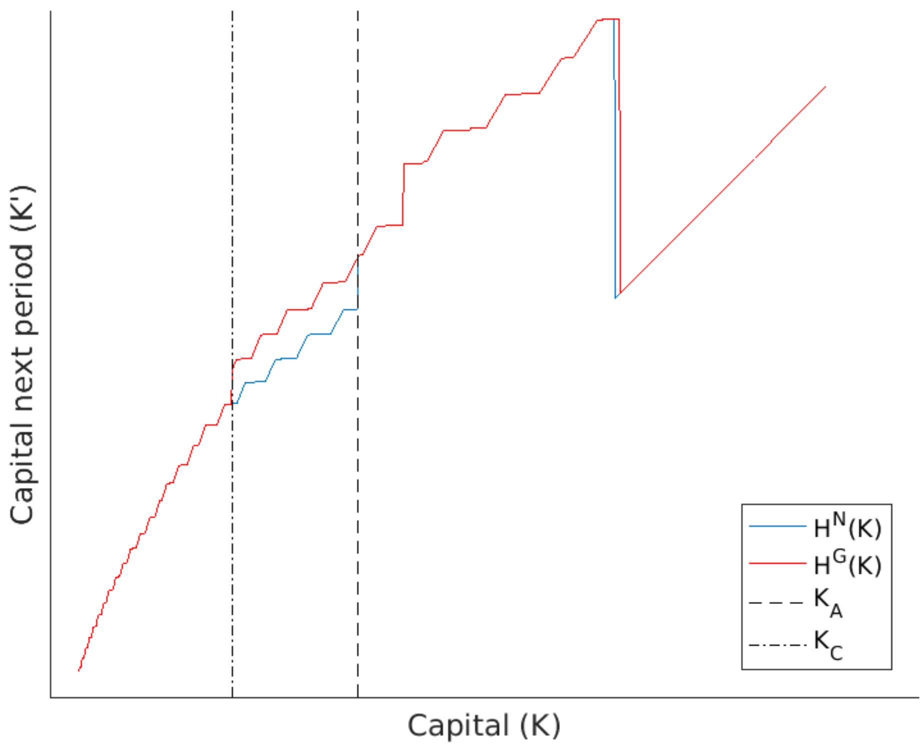
Another interesting case is shown in Figure 5.4, which shows the investment policies of plants with and without generators, holding the exogenous state constant. Differential investment responses are observed in the region between the adoption cutoff for non-generators K_A and the continuation cutoff for self-generators K_C, with self-generating plants investing more than their non-generating counterparts. In the absence of sunk adoption costs, K_A and K_C should be equal and investment responses wouldn't vary across plants. Therefore, irreversibilities could play an important role in explaining the differential patterns of investment between non- and self-generating plants.

Figure 5.3: Typical Policy Function in Models of Investment with Non-convex and Convex Adjustment Costs



Plots the policy function for a plant conditional on productivity in a model with both fixed and quadratic adjustment costs (described in Equation 5.15).

Figure 5.4: Typical Policy Function in Models of Investment with Non-convex and Convex Adjustment Costs



Plots the policy function for a plant conditional on productivity in a model with both fixed and quadratic adjustment costs (described in Equation 5.15).

CHAPTER 6

ESTIMATION: MAHARASHTRA AND PUNJAB

As electricity shortages vary substantially across states and depend largely on state-level policies, a strong argument can be made for estimating the model at the state level. In particular, I estimate the model separately for two states, Maharashtra and Punjab.

Table 6.1 provides a descriptive comparison of the two states. Maharashtra is India's largest state and economically the most important, accounting for 16% of India's annual GDP on average. Maharashtra also reports high levels of shortages annually, at a 16% average. Finally, manufacturing is important in Maharashtra, accounting for 22% of GSDP. In contrast, Punjab is smaller (accounting for 3% of the country's GDP), poorer (with a GSDP per capita of approximately 80% that of Maharashtra's), and more agriculture dependent (25% of GSDP vs. 9% for Maharashtra). Punjab also reports high levels of shortages at an average of 8% annually. I focus on the period 2006-2012 for both states.

Table 6.1: Descriptive Comparison of Maharashtra and Punjab

	Maharashtra	**Punjab**
GSDP (billion INR)	6,800.29	1,392.66
GSDP(% of India GDP)	0.16	0.03
Population (millions)	110.45	28.48
GSDP per capita (INR)	61,363.13	48,749.39
Manu. Sector (% of GSDP)	0.22	0.19
Ag. Sector (% of GSDP)	0.09	0.25
Electricity Cons. (GWh)	80,760.37	31,236.98
Electricity Cons. per Capita (kWh)	728.38	1094.72
Average Shortage	0.16	0.08

Descriptive statistics for Maharashtra and Punjab. All quantities computed as averages from annual data spanning 2006-2012.

By estimating the model at the state level, I aggregate over potential differences in investment dynamics across industries. However, given the small sample sizes for many industry-state pairs and that electricity market policies are largely the responsibility of the state governments, the aggregate analysis is likely to be more informative of state-level outcomes. Hence, state-level estimation and counterfactual analyses are appropriate for the purposes of this work.

Going forward, I detail the procedure for estimating the dynamic model from chapter 5 for the two states. Estimation proceeds in three steps: First, I estimate the production function and productivity process. Then, I estimate the shortage process using the CEA monthly frequency shortage data. Using the production function and shock process estimates, I then estimate the capital adjustment and generator costs parameters using Simulated Method of Moments (SMM). I calibrate three parameters in advance: First, I calibrate the (monthly) discount factor $\rho = 0.99$. I calibrate state specific depreciation rates δ using the average reported depreciation rate from the ASI. Next, because diesel is the primary fuel used in on-site generators, I calibrate the relative price of self-generated electricity p_g^t using a combination of diesel price series from the World Bank and reported grid electricity prices from the ASI.[1] Lastly, I assume all input prices are fixed, so the only random variables are productivity and electricity shortages.

6.1 Production Function Estimation

I estimate the production function coefficients using a combination of first-order conditions and dynamic moment conditions (as suggested by Ackerberg et al., 2015). Specifically, I use first order conditions implied by the static production model from chapter 5 to estimate the revenue elasticities for labor, materials and electricity. Rearranging the first order condition

1. From the WBES 2005, the reported cost of self-generated electricity is approximately INR 7 per kWh. An approximately 10 kWh/liter energy content of diesel, the WBES price implies that generators convert 40% of the diesel fuel energy content to electricity. I assume the same energy content and conversion factor to compute p_g for the full sample.

for labor yields

$$\beta_l = \begin{cases} \frac{w_t L_{it}}{A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} \int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e}} & = \frac{w_t L_t}{Y_{it}}, \quad \text{no generator} \\ \frac{w_t L_t}{A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} \left(\int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e} d\tau + \int_0^{B_t} M_{iGt\tau}^{\beta_m} E_{iGt\tau}^{\beta_e} d\tau \right)} & = \frac{w_t L_{it}}{Y_{it}}, \quad \text{generator,} \end{cases} \tag{6.1}$$

where $w_t L_{it}$ and Y_{it} are plant i's total labor expenditure and revenue in period t. Similarly, rearranging and integrating the first order conditions for materials and electricity yields

$$\beta_m = \begin{cases} \frac{p_t^m \int_0^{1-B_t} M_{it\tau} d\tau}{A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} \int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e}} & = \frac{p_t^m M_{it}}{Y_{it}}, \quad \text{no generator} \\ \frac{p_t^m \left(\int_0^{1-B_t} M_{it\tau} d\tau + \int_0^{B_t} M_{iGt\tau} d\tau \right)}{A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} \left(\int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e} d\tau + \int_0^{B_t} M_{iGt\tau}^{\beta_m} E_{iGt\tau}^{\beta_e} d\tau \right)} & = \frac{p_t^m M_{it}}{Y_{it}}, \quad \text{generator} \end{cases} \tag{6.2}$$

$$\beta_e = \begin{cases} \frac{p_t^e \int_0^{1-B_t} E_{it\tau} d\tau}{A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} \int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e}} & = \frac{p_t^e E_{it}}{Y_{it}}, \quad \text{no generator} \\ \frac{p_t^e \int_0^{1-B_t} E_{it\tau} d\tau + p_t^g \int_0^{B_t} E_{iGt\tau} d\tau}{A_{it}^{\eta} K_{it}^{\beta_k} L_{it}^{\beta_l} \left(\int_0^{1-B_t} M_{it\tau}^{\beta_m} E_{it\tau}^{\beta_e} d\tau + \int_0^{B_t} M_{iGt\tau}^{\beta_m} E_{iGt\tau}^{\beta_e} d\tau \right)} & = \frac{p_t^e E_{it} + p_t^g E_{iGt}}{Y_{it}}, \quad \text{generator,} \end{cases} \tag{6.3}$$

where the numerators are total expenditure on material inputs or electricity. Therefore, the labor, material, and electricity coefficients can be estimated directly using revenue shares without needing to observe electricity shortages. Since they are more robust to outliers, I use median revenue shares to estimate these three coefficients.

Since capital is a dynamic input, a static first-order condition cannot be used to estimate β_k. Furthermore, a linear regression of revenue on capital could lead to a biased estimate of β_k as plants' capital choices likely depend on unobserved productivity. Instead, I estimate β_k using moment conditions similar to those from the second stages of Olley and Pakes (1996) and Levinsohn and Petrin (2003). The estimation procedure is as follows.

First, define residualized revenue as

$$\tilde{y}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_e e_{it}, \tag{6.4}$$

where l_{it}, m_{it} and e_{it} are log employment, materials and electricity respectively. $\hat{\beta}_l$, $\hat{\beta}_m$ and $\hat{\beta}_e$ are the revenue elasticity estimates from the first order conditions. Then,

$$\tilde{y}_{it} = \beta_k k_{it} + \tilde{a}_{it}, \tag{6.5}$$

where $\tilde{a}_{it}$ is TFP. Following the assumptions of the model, TFP follows an AR(1) process.[2] Hence,

$$\tilde{a}_{it} = \tilde{\rho}\tilde{a}_{i,t-1} + \zeta_{it}. \tag{6.6}$$

Given that capital becomes productive with a lag (reflecting the time-to-build assumption), the capital stock k_{it} at time t should be independent of the innovation to productivity ζ_{it}. The natural implication is that the moment condition

$$\mathbb{E}\left[k_{it}\zeta_{it}\right] = 0 \tag{6.7}$$

can be used to estimate β_k using GMM. Given the estimate $\hat{\beta}_k$, productivity can be recovered from

$$\tilde{a}_{it} = \tilde{y}_{it} - \hat{\beta}_k k_{it}. \tag{6.8}$$

The fact that the shortage shock is not explicitly included in the estimation merits attention. In particular, the estimated TFP $\tilde{a}_{it}$ is a composite of the primitive TFP a_{it} from the model and potentially the realized shortage shock B_t. If B_t does not affect $\tilde{a}_{it}$, then the latter is analogous to the a_{it} from the model. Because Allcott et al. (2016) do not find a statistically significant effect of shortages on revenue productivity (and the magnitude of

2. Note that the estimation strategy does not depend on the assumption of an AR(1) process for productivity. A general first-order Markov process could be assumed and would yield the same estimating moment condition.

their estimate is considerably smaller than that on revenues), I assume $a_{it} = \tilde{a}_{it}$ and then estimate the AR(1) process for a_{it} using OLS.

Table 6.2 reports the values for calibrated parameters (Panel A), production function estimates (Panel B), and TFP process estimates (Panel C) for Maharashtra and Punjab. Differences in the estimates of the revenue elasticities reflect differences in technology and industry composition between the two, with Maharashtra being substantially more capital intensive ($\hat{\beta}_k = 0.17$ compared to 0.094 for Punjab) while being less materials intensive ($\hat{\beta}_m = 0.69$ versus 0.77). Because the effect of shortages on profits depends on the revenue shares of adjustable inputs, the production function estimates would imply plants in Punjab suffer lower losses than those in Maharashtra given the same shortage level. Furthermore, despite not being imposed during estimation, the estimates provide strong evidence for decreasing returns to scale.

6.2 Estimation of Shortage Shock Process

I interpret the shortage variable B_t as reflecting the percentage difference between aggregate electricity demanded and supplied at the regulated price level. As described in chapter 5, B_t^* denotes this demand-supply gap and follows an AR(1) process for computational convenience. When B_t is always strictly positive, the parameters for the aggregate shortage shock process can be recovered using OLS. In a series where $B_t = 0$, Simulated Maximum Likelihood can be used to recover the parameters for the B_t^* process.[3]

Given the short time period of the state annual shortage panel (15 years), I use the monthly frequency shortage data to estimate the shortage shock process at the state level. Figure 6.1 plots the raw monthly shortage data for both states.

Neither Maharashtra nor Punjab reports any zero shortages, and therefore I directly estimate the AR(1) process for each state separately without correcting for potential censoring. Estimates for Maharashtra and Punjab are reported in Table 6.3. The lag dependence of the

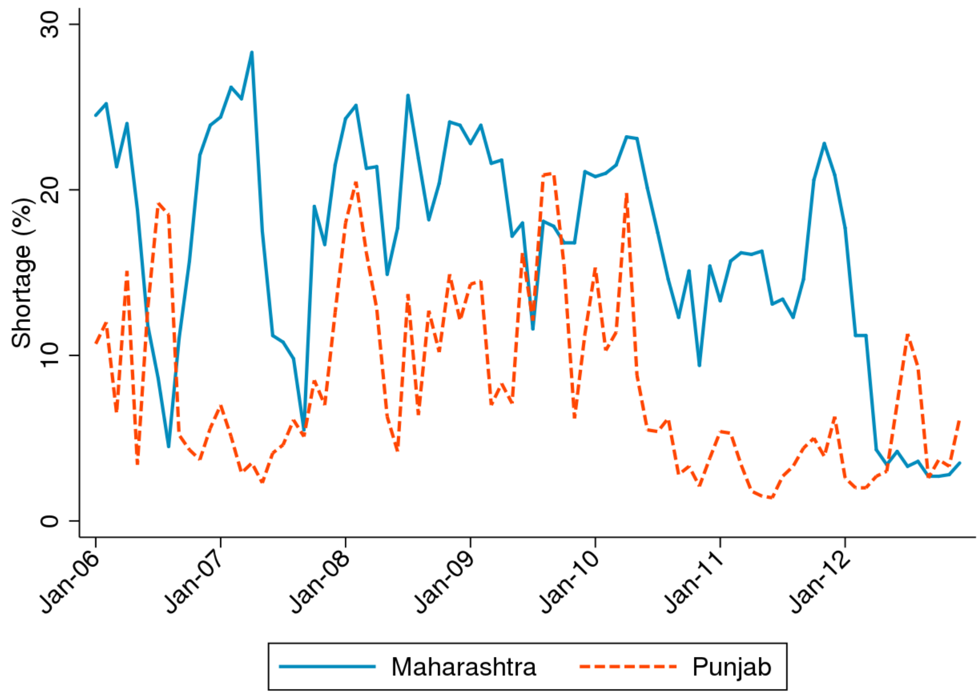
3. See Lee (1999).

Table 6.2: Static Parameters: Calibrated and Estimated Values

	Maharashtra	Punjab
Panel A. Calibrated Parameters		
ρ	0.99	0.99
δ	0.156	0.160
p_g/p_e	1.22	1.81
Panel B. Production Function Estimates		
Labor $\hat{\beta}_l$	0.0722	0.0734
	(0.000717)*	(0.00107)*
Materials $\hat{\beta}_m$	0.693	0.772
	(0.00200)*	(0.00256)*
Electricity $\hat{\beta}_e$	0.0211	0.0324
	(0.000282)*	(0.000570)*
Capital $\hat{\beta}_k$	0.176	0.0939
	(0.00467)*	(0.00347)*
Returns to Scale $1 - \hat{\eta}$	0.963	0.972
Panel C. TFP Process Estimates		
Mean $\hat{\mu}_a$	0.618	0.643
	(0.0460)*	(0.0750)*
Persistence $\hat{\rho}_a$	0.752	0.697
	(0.0188)*	(0.0367)*
Volatility $\hat{\sigma}_a$	0.264	0.230

Reports the values for calibrated parameters (Panel A), production function estimates (Panel B) and TFP process estimates (Panel C). Bootstrapped standard errors are reported for $\hat{\beta}_k$. * p<0.01.

Figure 6.1: Monthly Shortage Data: Maharashtra and Punjab Series



Raw monthly shortage data for Maharashtra and Punjab.

estimated residuals reveals that AR(1) is a good fit for both states (Figures C.1 and C.2).[4]

6.3 Estimation of Dynamic Parameters

The remaining "dynamic" parameters to be estimated include the capital adjustment cost as well as the generator adoption and maintenance cost parameters. The model has no analytical solution and therefore does not yield analytical moment conditions that can be used for estimation. Instead, I use SMM to estimate these cost parameters. Specifically, I solve for the vector of parameters that minimizes the (weighted) distance between the simulated moments generated by the model and the empirical counterparts of those moments. Formally, let $\hat{\Omega}$ be a vector of empirical moments from the data (in this case, the ASI-CEA

4. To account for potential seasonality, month fixed effects can be included in the AR(1) specification of the shortage shock process. Figures C.3 and C.4 show the residual autocorrelations after fitting such a process. Allowing for seasonality only slightly improves the fit for Maharashtra and doesn't seem to affect the fit for Punjab.

Table 6.3: AR(1) Process Estimates for Shortages

	Maharashtra	Punjab
ρ_s	0.847	0.645
	(0.0622)***	(0.0848)***
μ_s	0.0232	0.0284
	(0.0112)**	(0.00830)***
σ_s	0.0373	0.0416
Adj-R^2	0.692	0.409

Robust standard errors reported. *** p<0.01, ** p<0.05, * p<0.1.

merged panel) and let $\Omega(\phi)$ be the same moments from a simulated dataset for a vector of parameters ϕ. Then, the SMM estimator is defined as

$$\hat{\phi} = \arg\min_{\phi \in \Phi} \, (\hat{\Omega} - \Omega(\phi))' W (\hat{\Omega} - \Omega(\phi)), \tag{6.9}$$

where W is a weighting matrix. Generating the simulated moments $\Omega(\phi)$ requires numerically solving the dynamic model given parameters ϕ and then simulating the investment and generator adoption behavior of plants. I use all parameters estimated in the first two steps as fixed inputs for the simulations, and only estimate the dynamic cost parameters in this stage. I also estimate an additional parameter λ that captures the incidence of the shortage process on plants, making the full vector of seven parameters $\phi = \left(C_K^F, C_K^Q, C_G^{A,F}, C_G^{A,V}, C_G^{M,F}, C_G^{M,V}, \lambda\right)$.

In principle, the model could be estimated directly using the shortage shock process from the previous estimation step. However, doing so would require the assumption that the CEA shortage variable represents the "true" electricity shortage faced by plants. The CEA data is compiled independently of the ASI and since the measured shortage is computed using the aggregate demand and supply of electricity, it may mask over potential differences in the allocation of shortages across sectors i.e. the aggregate shortage may not reflect the manufacturing sectoral shortage. For example, a more industry friendly state (like Maharashtra) may preferentially allocate electricity to the manufacturing sector, while agriculture dependent states (like Punjab) may allocate more shortages to industry in times of scarcity. Therefore, I instead allow the manufacturing sectoral shortage to be a linear function of the aggregate shortage level; for an observed shortage B, the shortage shock faced by plants is λB.[5] As with the other parameters, I allow λ to vary by state and therefore allow for a differential allocation of shortages between the two states.

6.3.1 Moment Selection

Identification of the model's parameters relies heavily on the choice of moments used to estimate them. In particular, the moments should be differentially informative about the underlying parameters so as to have a full-rank set of moments required for consistent estimates of the parameter vector ϕ. Broadly, the presence of differences in size and investment behavior of plants with and without generators suggests using a combination of dynamic and cross-sectional moments would be most informative of the adjustment and generator costs parameters. Though the selected moments jointly identify the elements of ϕ, I detail the moment-selection process and describe the intuition guiding the choices in the rest of this section.

The first moment of choice is the coefficient from a first-difference regression of plant-level (log) grid electricity consumption on the shortage measure. As the ASI and CEA collect and publish their data independently, this moment is chosen to capture the informativeness of the shortage measure for ASI plant behavior, specifically capturing the incidence λ of "shortage"

5. The "true" shortage could also be modeled as a more flexible function of the observed shortage measurement. Given the limited variation in the data and the computation-intensive nature of estimation, however, I focus on the linear case as capturing the average incidence of shortages on manufacturers across states. Additionally, the assumption of linearity doesn't affect the interpretation of the shortage process parameters.

on plants. Regressing in first-differences nets out persistent level-differences between plants in both the data and the simulations.[6,7] Of course, although primarily intended to inform the estimation of λ, this moment could still be affected by the investment response and therefore the capital adjustment frictions faced by plants.

To capture the adjustment cost parameters, I target moments of the investment rate distributions for plants with and without generators. Specifically, I target the probability of negative or (close to) zero investment, which I refer to as "inaction" in an abuse of terminology. Formally, I compute this moment as the probability that the investment rate $I/K < 0.03$. I also target large bursts of capital expenditures or "investment spikes" ($I/K > 0.2$). Similar moments have been used to estimate non-convex and convex adjustment costs in models of investment dynamics (Cooper and Haltiwanger, 2006; Asker et al., 2014). The intuition behind these moment choices is that high fixed costs of capital adjustment lead to infrequent investment in large amounts, whereas quadratic adjustment costs dampen this response. Furthermore, I target these moments separately for plants with and without generators, which is likely to capture the different returns to investment (depending on shortages, generator ownership, and generator variable maintenance costs) as well as the size composition of the different generating types of plants (depending on generator fixed costs and capital fixed costs). Therefore, I choose four moments from the investment rate distribution.

I also target two additional dynamic moments: first, the serial correlation of the investment rate, which has been shown to be sensitive to the specification of adjustment costs (Bloom, 2009); and second, I target the "generator continuation probability" or the probability that a plant owns a generator conditional on owning one in the previous period. The latter moment is specifically selected to be informative of the generator adoption cost,

6. In fact, the static model implies an approximately linear relationship between the log of grid electricity consumption and the shortage variable.

7. David and Venkateswaran (2019) use a similar first-difference regression coefficient as a moment to capture the effect of uncertainty on capital misallocation.

which creates irreversibility in generator adoption and leads to plants delaying the removal of generators in better shortage states.

Lastly, I target the generator ownership rate as well as the relative employment of non-generating firms (defined as the mean employment of plants without generators relative to the mean employment of plants with). The relative employment moment is particularly informative of the fixed components of generator costs, leading to a size gap between plants that adopt and own generators and those that don't. The overall ownership rate intuitively captures both components of generator costs.

Overall, I use nine moments to estimate seven parameters, leaving two over-identifying restrictions for the model's parameters. Table 6.4 tabulates the moments used to estimate the parameters for Maharashtra and Punjab. Given the higher level of reported shortage in Maharahstra, the lower covariance between grid electricity consumption and shortages as well as the somewhat surprisingly lower generator ownership rate suggest a potentially lower incidence of shortages on plants than in Punjab. The high rate of inaction in Punjab also suggests higher fixed costs of investment.

6.3.2 Estimation Details

For a given set of parameters, I discretize the state space and numerically solve the dynamic model for the value and policy functions using Value Function Iteration with linear interpolation in between states. Then, I use the policy functions to simulate the investment and generator take-up behavior of plants, creating a panel dataset that I use to construct simulated equivalents of the estimating moments.

I simulate 250 panels of 1,000 plants each for 20 years. Because shortages are market level shocks, all firms in each panel receive the same sequence of shortage shocks. To account for the effects of temporal aggregation, I assume that the shocks (shortage and productivity) are drawn and dynamic decisions (investment and generator) are made at the monthly frequency and then aggregate to the annual frequency to reflect the frequency of the ASI. As I rely on

Table 6.4: Empirical Moments for SMM Estimation by state

Moment	Maharashtra	Punjab
Reg. Coeff. for ΔE_{it} on $\Delta Shortage_t$	-0.947	-1.56
Inaction (non-generators)	0.359	0.536
Inaction (generators)	0.198	0.273
Investment Spike (non-generators)	0.333	0.275
Investment Spike (generators)	0.402	0.404
Investment Rate Serial Correlation	0.0404	0.0131
Generator Continuation Probability	0.618	0.757
Generator Ownership Rate	0.101	0.393
Rel. Emp. of Non-generators	0.244	0.497
Number of Plants	12221	6601
Number of Observations	25859	13262

Moments used for the SMM estimation of the dynamic parameters, for both Maharashtra and Punjab. Inaction is defined as $P(I/K) < 0.03$, investment spike is defined as $P(I/K) > 0.2$.

simulating the stationary distribution of the model, I simulate 120 years of data and only use the last 20 years to construct the estimating moments. Since the model (and therefore the moments) is potentially subject to discontinuities, I use a simulated annealing algorithm for estimation.

Although the SMM estimator will be consistent for any positive definite weighting matrix, the choice of W is important for the efficiency of the estimator. Following Lee and Ingram (1991), I use the efficient choice of W, which is the inverse of the variance-covariance matrix V of the data moments.[8] I use a block bootstrap routine with replacement to estimate V. I then use W to compute standard errors for the SMM estimator $\hat{\phi}$.

Given the static parameters are precisely estimated and bootstrapped standard errors would be intractable given the computational cost of estimating the model, I follow Bloom

8. Specifically, if V is the variance-covariance matrix of the data moments, the efficient choice of W is $\left(\left(1+\left\lfloor\frac{N_d}{N_s}\right\rfloor\right)V\right)^{-1}$, where N_d and N_s are the sample sizes of the data and simulated data respectively. Although not required for estimation, I include the constant term when computing standard errors.

(2009) and use numerical derivatives to compute standard errors for the SMM estimator $\hat{\phi}$. Specifically, I compute

$$\frac{\partial \Omega(\hat{\phi})}{\partial \phi} \approx \frac{\Omega(\hat{\phi}(1+\varepsilon)) - \Omega(\hat{\phi})}{\hat{\phi}\varepsilon} \tag{6.10}$$

for some choice of ε. To ensure robustness to potential discontinuities in the derivatives, I compute them for $\varepsilon \in \{1\%, 2\%, 3\%, 5\%, -1\%, -2\%, -5\%\}$ for each parameter and report the median of the implied standard errors.

6.4 Dynamic Parameter Estimates

Table 6.5 reports the estimated values of the dynamic parameters for Maharashtra, and Table 6.6 compares the fitted moments to the actual moments for the same state. The "Opp. Cost" and "Fixed Cost" columns report estimates for the adjustment cost specifications given by (5.14) and (5.15) respectively. Table 6.5 also reports the objective criterion of the SMM estimation as a measure of the model's fit.

The fit criterion implies the opportunity cost specification is the best fit for Maharashtra, though both models fit similarly. Examining the fitted moment values in Table 6.6, the model is unable to replicate the lower inaction rate and more frequent investment spikes of self-generating plants, or the relative size of non-generating plants. This result is partly a reflection of the tension between self-generation and investment; larger plants are more likely to adopt generators due to the scale-invariant fixed costs, but also less likely to invest due to the fixed capital adjustment cost. Therefore, it is partly driven by the fact that the generator ownership rate in Maharashtra is low at 10% given the high reported levels of shortage, because the generator rate moment receives a relatively high weight in the estimation.[9]

9. Furthermore, because the generator ownership rate is low, the investment rate moments for self-generating plants also receive lower weight in the estimation due to the smaller sample size available. Therefore, the model is likely to fit data with intermediate values of generator ownership better than data with

Table 6.5: Dynamic Parameter Estimates for Maharashtra

	Opp. Cost	Fixed Cost
λ	0.717	0.829
	(0.0123)***	(0.0414)***
C_K^F	0.0915	0.00346
	(0.00700)***	(0.000177)***
C_K^Q	0.432	0.427
	(0.0239)***	(0.0175)***
$C_G^{A,F}$	0.0341	0.0145
	(0.0142)**	(0.0167)
$C_G^{A,V}$	0.0167	0.00930
	(0.00688)**	(0.00751)
$C_G^{M,F}$	0.0542	0.0899
	(0.00806)***	(0.00548)***
$C_G^{M,V}$	0.0907	0.0458
	(0.0117)***	(0.0106)***
Distance Criterion	1,533.220	1,588.221

Point estimates of incidence, adjustment cost and generator costs for Maharashtra. Distance criterion is the value of the SMM criterion $(\hat{\Omega} - \Omega(\hat{\phi}))'W(\hat{\Omega} - \Omega(\hat{\phi}))$ at the estimated parameter values. Standard errors computed using numerical derivatives. *** p $<$ 0.01, ** p $<$ 0.05.

Table 6.6: Estimated Model Fit for Maharashtra

	Opp. Cost	Fixed cost	Data
Reg. Coeff. for ΔE_{it} on $\Delta Shortage_t$	-1.128	-0.965	-0.947
Inaction (non-generators)	0.321	0.367	0.359
Inaction (generators)	0.432	0.512	0.198
Investment Spike (non-generators)	0.371	0.327	0.333
Investment Spike (generators)	0.311	0.225	0.402
Investment Rate Serial Correlation	0.0587	0.0349	0.0404
Generator Continuation Probability	0.537	0.589	0.618
Generator Ownership Rate	0.118	0.137	0.101
Rel. Emp. of Non-generators	0.651	0.568	0.244

Reports fitted and actual moments for different specifications of the fixed cost of investment. Relative differences from corresponding data moment are shown in parentheses.

The estimated shortage incidence parameter is less than unity at 0.717 and statistically significant, suggesting the "true shortage" shocks realized by plants are lower than that of the CEA shortage level. Since industry is a relatively important sector in Maharshtra's economy (particularly compared to agriculture), the point estimate of λ is consistent with Maharashtra being a more manufacturer-friendly state when allocating electricity during shortage times.

All generator cost parameters are also positive and statistically significant, implying substantial irreversibility and recurring costs associated with generator ownership. The magnitude of the fixed costs is particularly large, with the fixed adoption and maintenance cost components translating to 8.19% and 13.0% of the average plant's profitability absent shortages. The magnitudes are still large for self-generating firms (which tend to be larger and more profitable), amounting to 5.60% and 8.91% of the average self-generating plant's profitability. While the variable component of the adoption cost is low at 1.67% (though statistically significant), the variable cost of generator maintenance is also substantial at 9.07%

extreme values.

of profitability, implying that generator ownership is indeed a drag on plant profitability, lowering investment.

Turning attention toward the estimates for Punjab (Table 6.7), the fit criterion again implies the opportunity cost specification is the best fit for Punjab, though the fixed cost specification again gets close. However, compared to Maharashtra, the estimated model fits much better for Punjab with a much lower fit criterion.[10] Table 6.8 reports the fitted moments of the estimated model compared to the corresponding data moments and confirms the better fit, as the relative investment patterns by self-generation as well as generator ownership and relative size are matched better for Punjab.

Notably, the estimated incidence of shortages for Punjab is large at 2.086, consistent with the previous hypothesis that manufacturers in Punjab, the more agriculture-dependent state, would bear more of the burden of an aggregate shortage than in Maharashtra. The difference in the incidence parameter also partially explains why Punjab, despite reporting substantially lower shortages than Maharashtra, has a higher rate of self-generation. As expected given the higher rates of inaction, the fixed costs of capital adjustment are also higher in Punjab. The quadratic component is also higher, which dampens the response of investment to shocks more in Punjab.

Comparing the generator costs, the estimate of $C_G^{M,V}$ is close to that of Maharashtra at 10.1%, confirming that generators do indeed disrupt manufacturer activity, leading to lost profits. The fixed cost of $C_G^{M,F}$ is higher in Punjab, amounting to 23.08% of the average plant's profitability (and 19.12% of the average generating plant's profits). Though this estimate appears to be substantially larger than that for Maharashtra, the estimates are not quite comparable due to the differences in production technology and productivity levels in the two states. Though not statistically significant, the point estimates for the adoption cost parameters are also large for Punjab, with a variable adoption cost of 6.23% and a fixed cost

10. Note the fit criteria are not directly comparable across states due to differences in the weighting matrix. For comparison, a 10% deviation of all moments for Maharashtra would yield a distance criterion of approximately 338, whereas the same for Punjab would yield a distance criterion of approximately 283.

Table 6.7: Dynamic Parameter Estimates for Punjab

	Opp. Cost	Fixed Cost
λ	2.086	1.655
	(0.129)***	(0.0674)***
C_K^F	0.188	0.00502
	(0.0468)***	(0.000358)***
C_K^Q	0.361	0.236
	(0.0708)***	(0.0133)***
$C_G^{A,F}$	0.0203	0.00856
	(0.0225)	(0.00168)***
$C_G^{A,V}$	0.0623	0.00891
	(0.0927)	(0.00204)***
$C_G^{M,F}$	0.0982	0.131
	(0.00952)***	(0.00443)***
$C_G^{M,V}$	0.101	0.0402
	(0.0255)***	(0.00281)***
Distance Criterion	243.181	278.598

Point estimates of incidence, adjustment cost and generator costs for Punjab. Distance criterion is the value of the SMM criterion $(\hat{\Omega} - \Omega(\hat{\phi}))'W(\hat{\Omega} - \Omega(\hat{\phi}))$ at the estimated parameter values. Standard errors computed using numerical derivatives. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6.8: Estimated Model Fit for Punjab

	(1) Opp. Cost	(2) Fixed cost	(3) Data
Reg. Coeff. for ΔE_{it} on $\Delta Shortage_t$	-0.481	-0.753	-1.558
Inaction (non-generators)	0.592	0.491	0.537
Inaction (generators)	0.323	0.329	0.273
Investment Spike (non-generators)	0.256	0.283	0.275
Investment Spike (generators)	0.347	0.355	0.404
Investment Rate Serial Correlation	0.0305	0.0965	0.013
Generator Continuation Probability	0.651	0.643	0.757
Generator Ownership Rate	0.398	0.415	0.393
Rel. Emp. of Non-generators	0.719	0.767	0.497

Reports fitted and actual moments for different specifications of the fixed cost of investment.

equivalent to 4.78% (3.97%) of the profitability of all (self-generating) plants.

A natural question is whether the estimated generator costs are reasonable. This question is not straightforward to answer, particularly because the recurring maintenance costs capture broad opportunity costs and the adoption costs may reflect frictions in the generator market not captured by generator prices. Nevertheless, a reasonable comparison would be with generator purchase prices. Since I don't observe such prices in the ASI, I compare the estimated costs to the reported generator prices from the WBES 2005 in the following way. First, I convert sales from the WBES to profits using the production function estimates for each state. Then, I convert generator purchase prices into profit shares, which I compare to the estimated generator cost parameters.[11] Table 6.9 reports the adoption and maintenance cost estimates along with the WBES mean and median generator purchase prices. All quantities are reported as shares of the average self-generating plant's profits.

The median WBES price is substantially lower than the mean, consistent with fixed components of purchase prices driving up the profit share for small plants, skewing the distribu-

11. To prevent mis-measurement due to inflation, I only use generators purchased from the year 2000 onwards in the WBES. Data for generator purchase prices were not available in the WBES 2014.

Table 6.9: Comparison of implied generator costs to WBES Generator Purchase Prices

	$C_G^{A,F}$	$C_G^{A,V}$	Total	WBES Mean	WBES Median
Maharashtra	5.60	1.67	7.27	21.69	6.86
Punjab	3.97	6.23	10.20	37.90	11.98

	$C_G^{M,F}$	$C_G^{M,V}$	Total	WBES Mean	WBES Median
Maharashtra	8.91	9.07	17.98	21.69	6.86
Punjab	19.12	10.10	29.22	37.90	11.98

All numbers reported as a percentage of the average self-generating plant's variable profits.

tion of generator prices relative to profits. This additionally supports the parametrization of generator costs in the model. Furthermore, the magnitudes from Table 6.9 suggest the estimates of the generator costs are not unreasonable, with the adoption costs being comparable to the median WBES costs. The maintenance costs are relatively large but predictably so, since it encompasses opportunity costs not captured by purchase or rental prices.

Another comparison worth attention is that of the adjustment costs to others estimated in the literature. Asker et al. (2014) estimate the same adjustment cost specification (without generators) for India using a different panel of firms for the period 1989-2003. Their estimate of the countrywide fixed cost (0.12) is close to my estimates for both states (0.0915 and 0.188). The same authors' estimate of the quadratic cost is an order of magnitude higher at 3.46, though they observe a lower spike rate in their data than I do, which rationalizes the difference. They also make different assumptions regarding the curvature of the profit functions, which would also partly explain the difference. Comparing to Cooper and Haltiwanger (2006), their estimate of the fixed cost for U.S. establishments is slightly higher (0.204) while that of the quadratic cost is lower (0.049). Beyond these two examples, a wide range of adjustment costs have been estimated in the literature and my estimates fall reasonably within that range.

6.4.1 Discussion of Estimates

The interpretation of the estimates are subject to a few caveats. First, the estimation relies on the CEA shortage data accurately reflecting the shortage shock process faced by plants. The CEA data is informative, as shown in this study and in (Allcott et al., 2016). However, the monthly shortage series may not perfectly capture the manufacturing sector shortage shock process. While the inclusion of the "incidence" parameter in the estimation allows for some flexibility in how the CEA shortage variable maps to realized shortages in the model, it does not allow for the incidence to vary by shortage level or across plants. These omitted features could potentially bias the estimates of generator costs upwards if, for example, large plants receive preferential access to electricity during shortage states.

Second, the assumption of independence between the productivity and shortage shocks could be another source of bias if violated. For example, a high aggregate productivity shock could lead to greater demand for grid electricity and consequently higher shortages. In such a case, productivity and shortages could be positively correlated and bias the adjustment and generator cost estimates (though the direction of bias is unclear). Although I don't model the general equilibrium effects due to the computational costs of estimation, the introduction of correlated shocks is potentially a good approximation for such effects, and a richer dataset would allow for the inclusion of such a feature.

Lastly, I don't allow for other margins of adjustment such as the outsourcing of intermediates as in Fisher-Vanden et al., 2015. To the extent that these adjustments don't vary intertemporally, they should be captured by λ; however, the model cannot account for non-investment dynamic adjustments. Although a richer model could accommodate these features with plant-level data, I am unable to do so given the limited variation in the CEA data. I also do not model entry and exit, or the behavior of the informal sector, both of which could affect the aggregate analysis. Thus, the estimates and forthcoming counterfactual analyses should be interpreted as applying to the existing formal manufacturing plants.

CHAPTER 7

COUNTERFACTUALS

In this chapter, I proceed to describe the counterfactual analyses I conduct using the estimates from chapter 6. I focus on three counterfactuals: assessing the long-run impact of electricity shortages, a policy counterfactual that involves dynamic electricity pricing to correct for shortages, and the impact of volatility in the shortage process. Since the model outcomes are computed from the stationary distribution of plants, any difference between the baseline economy and a counterfactual economy should be interpreted as a long-run differences in outcomes.

7.1 Long-Run Cost of Shortages

With the estimated model in hand, I am able to approach the main motivating question of this research: What is the long-run cost of electricity shortages? The relevant counterfactual to evaluate this long-run impact of shortages is to set the shortage incidence parameter $\lambda = 0$.[1] A simulation of the model with $\lambda = 0$ holding the rest of the parameters constant at their estimated values should produce the counterfactual investment behavior of plants in the absence of shortages, allowing me to assess the impact of shortages on the investment behavior of plants. Furthermore, I am able to use the static model of production to map this investment behavior into counterfactual value added and producer surplus outcomes, allowing me to quantify the long-run welfare and value added effects. Table 7.1 shows the changes in value added, producer surplus, and the mean investment rate (for the estimated λ relative to $\lambda = 0$) for both the states.

The first column of Table 7.1 reports the difference allowing for endogenous plant investment, while the second and third columns report the static differences assuming investment decisions were exogenous. The second column specifically reports the static differences im-

1. Equivalently, μ_B and σ_b could both be set to 0.

Table 7.1: Counterfactual Outcomes without Shortages

	(1) Dynamic	(2) Static (model)	(3) Static (ACO)
Panel A. Maharashtra			
Δ Value Added (%)	-52.27	-13.98	-16.40
Δ Producer Surplus (%)	-43.59	·	·
Δ Mean Investment Rate (p.p.)	-7.089	·	·
Panel B. Punjab			
Δ Value Added (%)	-63.64	-23.75	-7.419
Δ Producer Surplus (%)	-57.12	·	·
Δ Mean Investment Rate (p.p.)	-11.01	·	·

Reports the change in value added, producer surplus and the mean investment rate for Punjab and Maharashtra for $\lambda = 0 \rightarrow \lambda = \hat{\lambda}$ for Punjab and Maharashtra. Changes are reported in percentages for value added and producer surplus, and percentage points for the mean investment rate. Column (2) reports the implied static losses assuming the estimated incidence $\hat{\lambda}$ while column (3) reports the static losses using a revenue elasticity -1.091 estimated by ACO assuming $\lambda = 1$.

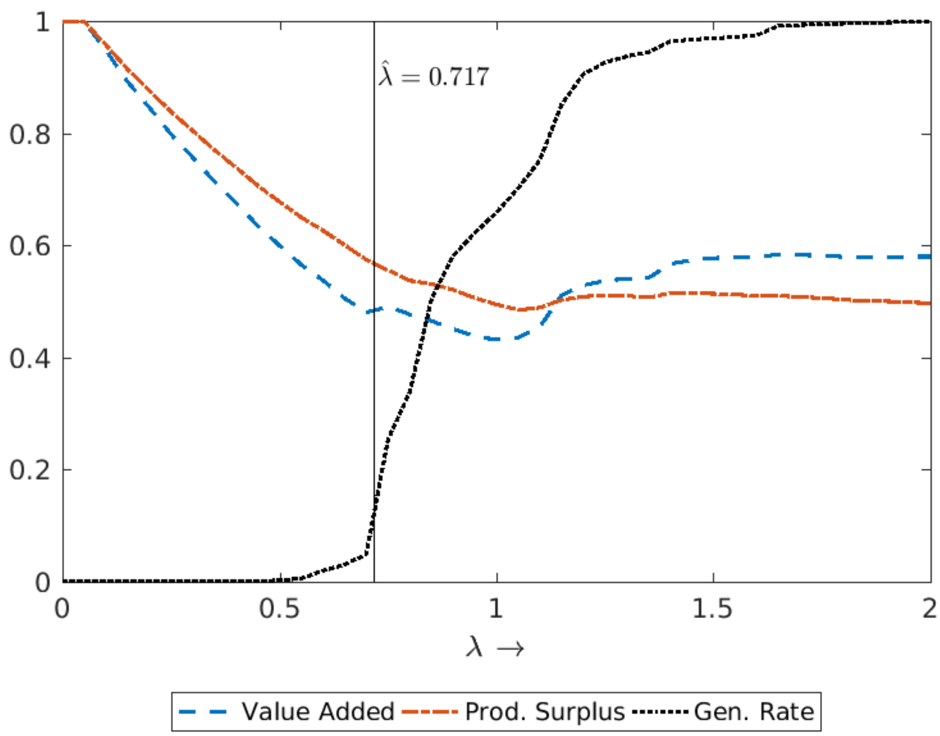
plied by the model. For the third column, I use the estimated causal effect of the CEA's shortage variable on revenues from Allcott et al. (2016) to compute the implied static losses. The third column should be interpreted with caution, as the authors estimate an average effect over all states for a different time period (though their sample period of 1992-2010 encompasses most of mine). Nevertheless, it serves as a useful benchmark for comparison. Note here that value added is defined as revenues less the cost of intermediates (materials and electricity), and producer surplus is defined as variable profits less the costs of capital adjustment and generator adoption or maintenance.

First focusing on Maharashtra, the estimated model implies substantial value added and producer surplus losses relative to the economy without shortages at 52.27% and 43.59% respectively. Investment, measured by the mean investment rate, is also considerably lower, by 7 percentage points. Compared to the static losses (13.98% - 16.40%), the losses when taking dynamic adjustments into account are much larger. The losses for Punjab are comparable at 63.64% and 57.12% of value added and producer surplus, respectively. Those losses are also accompanied by an 11.01 p.p. reduction in the mean investment rate. For both states, the estimates suggest that accounting for dynamic responses is highly important: The long-run losses associated with electricity shortages are 2.5 - 3.5 times larger than the static losses in terms of value added.

To better understand how shortages affect long-run output and producer welfare, Figures 7.1 and 7.2 plot aggregate value added, producer surplus and the generator ownership rate as a function of the incidence, λ (note $\lambda = 4$ in Punjab is roughly equal to a $\lambda = 2$ for Maharashtra, given the differences in the average shortage).

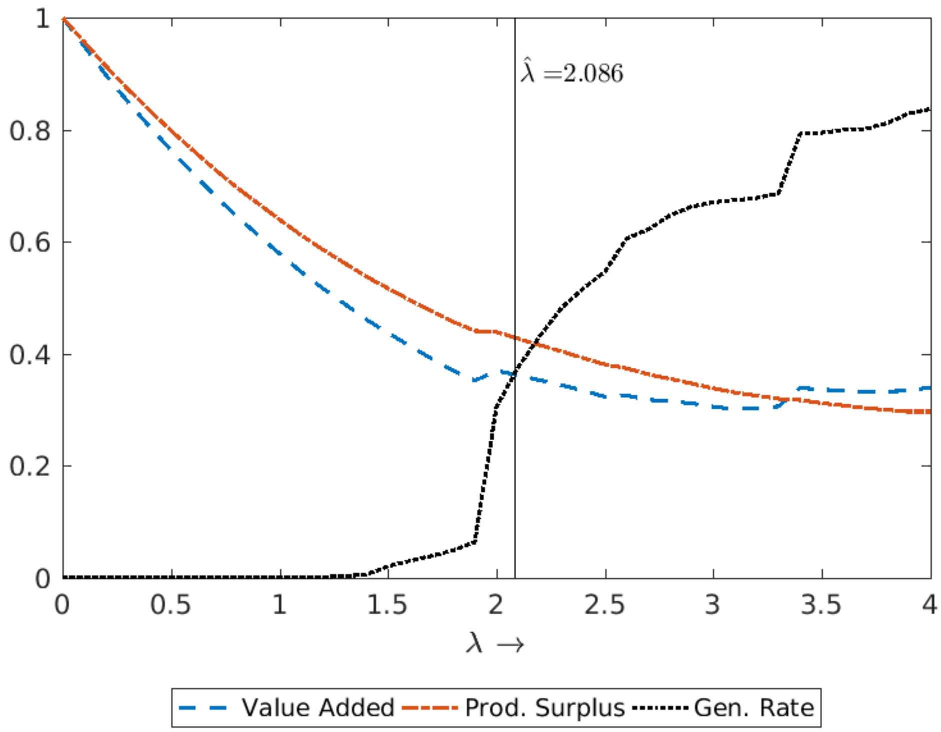
An interesting pattern emerges for value added as λ increases: An increase in shortages leads to a decrease in value added but also an increase in generator take-up. As a result, although value added initially decreases sharply as λ increases, it recovers as generator ownership rises, leading to a slight increase in output once λ gets large enough. This pattern is reflected in both states, driven by two forces: First, plants are insured against shortage

Figure 7.1: Change in Value Added, Producer Surplus and Generator Adoption with λ: Maharashtra



Plots the changes in value added and producer surplus (relative to $\lambda = 0$) and the generator ownership as functions of λ for Maharashtra.

Figure 7.2: Change in Value Added, Producer Surplus and Generator Adoption with λ: Punjab

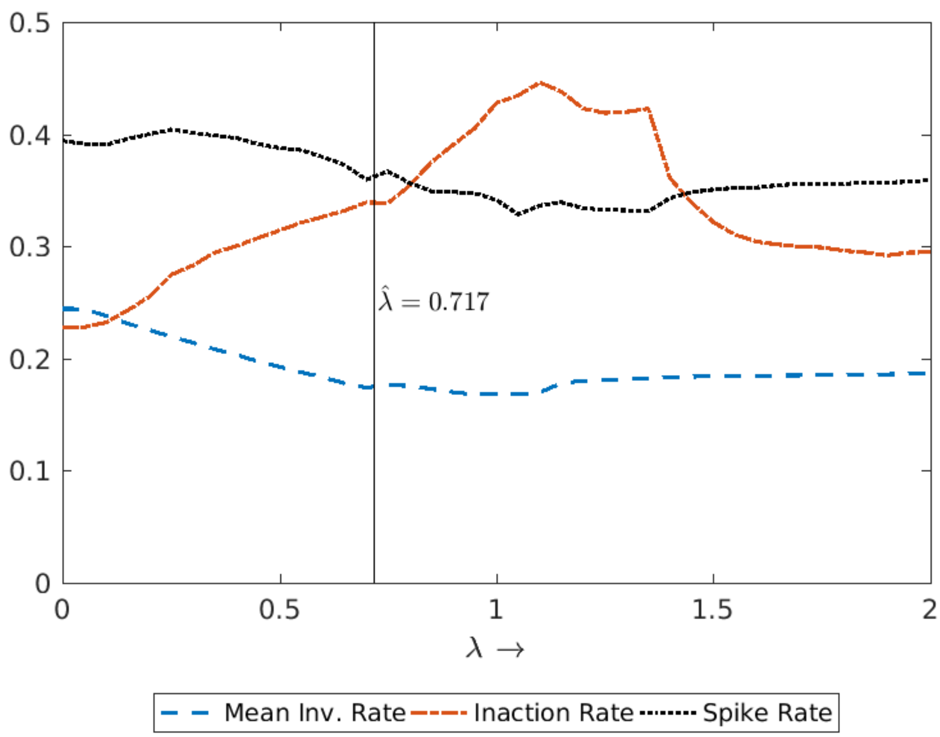


Plots the changes in value added and producer surplus (relative to $\lambda = 0$) and the generator ownership as functions of λ for Punjab.

shocks, raising the returns to investment in productive capital; and second, plants also face a distorted incentive to stay large due to the fixed costs of generator ownership. However, producer surplus doesn't recover but rather flattens out as plants start incurring the costs of generator ownership (which don't vary with λ, effectively bounding the producer welfare losses) instead of the cost of shortages.

The comparative statics from above are reflected in the aggregate investment behavior of plants. Figures 7.3 and 7.4 plot the mean investment, inaction, and spike rates for both states on the same λ scales.

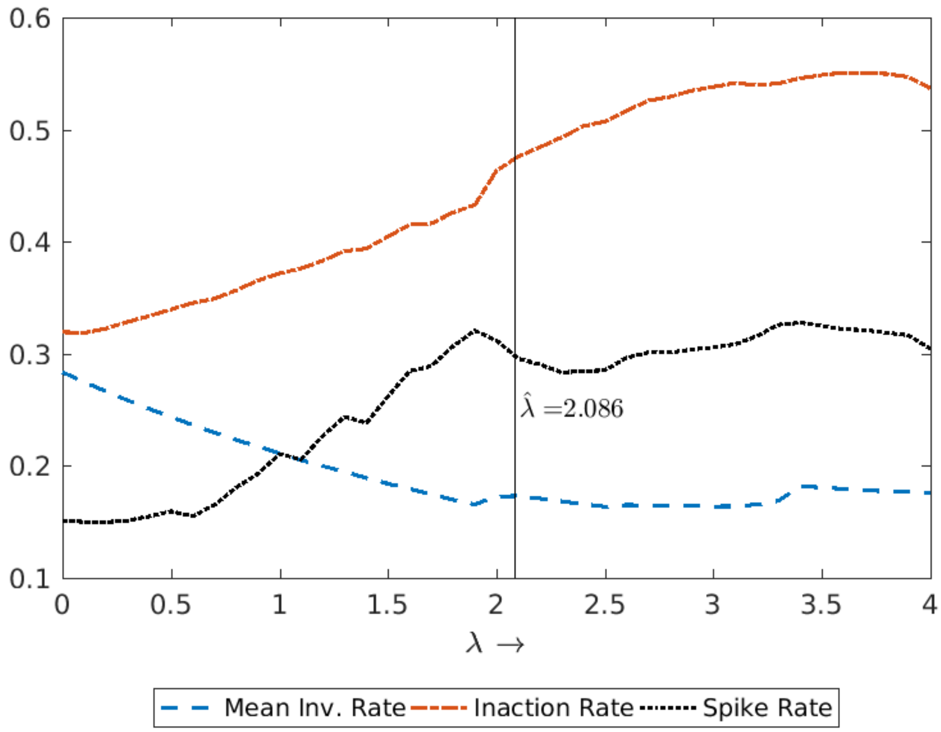
Figure 7.3: Change in Investment Behavior with λ: Maharashtra



Plots the changes in the mean investment rate, investment inaction and spike rates as functions of λ for Maharashtra.

Although the other two series display similar behavior, the non-monotonic response due to generator adoption is clearest for the inaction rate. As expected, the inaction rate increases as λ increases, consistent with a decrease in the returns to investment. This increase is

Figure 7.4: Change in Investment Behavior with λ: Punjab



Plots the changes in the mean investment rate, investment inaction and spike rates as functions of λ for Punjab.

more pronounced in Punjab due to the high fixed adjustment cost. However, as more plants adopt generators, fewer plants are exposed to shortages in aggregate, leading to a subsequent decrease in the inaction rate.

Altogether, the main takeaways here are that first, the dynamic costs of electricity shortages are potentially very large compared to the static costs. Second, while generator adoption can mitigate the output effects of shortages, self-generation still reduces producer welfare. The latter suggests that policies that encourage or subsidize generator take-up may not be useful, because the recurring costs of generator ownership are high and welfare reducing.

7.2 Dynamic Pricing

Next, I study the implications of a dynamic electricity pricing policy that prevents shortages. In particular, I study a dynamic pricing policy that allows monthly electricity prices to vary and therefore clear electricity markets, leading to monthly shortages being realized as electricity price shocks rather than utilization shocks (as in the model from chapter 5). Compared to the stylized economy from the previous counterfactual (where electricity markets clear without price adjustments), dynamic pricing more realistically reflects efficient electricity markets where prices adjust to equate electricity demand and supply.

Intuitively, because electricity is a small component of plants' costs, electricity price shocks should have more moderate effects on the profits and therefore the investment behavior of plants. As I don't model any general equilibrium effects or electricity supply, I approximate dynamic pricing in my framework the following way.

I assume that electricity supply is perfectly inelastic in each month. Conditional on the regulated price level of electricity p_E, a shortage of B_t is anticipated in period t. Under a dynamic pricing scheme, the price of electricity is allowed to deviate from p_E such that the daily demand for electricity for all plants is reduced by exactly B_t. Specifically, daily electricity demand for electricity is given by

$$E_{it\tau} \propto \left(\frac{1}{p^e}\right)^{(\beta_E+\beta_K+\eta)/(\beta_K+\eta)}, \tag{7.1}$$

when $B_t = 0$. Now, suppose the price regulator accurately anticipates the shortage $B_t > 0$ and chooses a new price $p^e \exp(\tilde{p}(B_t))$ such that daily electricity demand is reduced by a fraction B_t for all plants. Here, $\tilde{p}(B_t)$ is the percentage deviation of price from p^e required to prevent a shortage of B_t. Then, from (7.1), taking logs and differencing yields

$$\tilde{p}(B_t) = \frac{\beta_k + \eta}{\beta_e + \beta_k + \eta} B_t. \tag{7.2}$$

Therefore, under a dynamic pricing regime where the shortage shock is realized as electricity price shocks only, the profit function of a plant without a generator is given by

$$\tilde{\Pi}^N(K_{it}, A_{it}, B_t) = \left(\frac{1}{\exp(\tilde{p}(B_t))}\right)^{\beta_e/(\beta_k+\eta)} \pi(K_{it}, A_{it}), \tag{7.3}$$

where $\pi(\cdot)$ is the plant's profitability as defined earlier in (5.9). Plants may still adopt generators in cases when the price deviations for grid electricity are large; that is, self-generated electricity becomes cheaper than grid electricity (as suggested by Rud, 2012b). Therefore, plants with generators decide to produce using either self-generated electricity or grid electricity for the entire period (because the relative price of grid electricity does not vary within period, it is optimal for self-generating plants to just choose the lower cost option). Then, letting $p^g = p^e \exp(\tilde{p}^g)$, the profits of plants with generators is given by

$$\tilde{\Pi}^G(K_{it}, A_{it}, B_t) = \left(\max\left\{\frac{1}{\exp(\tilde{p}(B_t))}, \frac{1}{\exp(\tilde{p}^g)}\right\}\right)^{\beta_e/(\beta_k+\eta)} \pi(K_{it}, A_{it}). \tag{7.4}$$

The rest of the structure of the dynamic model remains the same. Using the estimated parameters from chapter 6, I simulate the model using the dynamic pricing policy with the profit functions from (7.3) and (7.4).

Note that dynamic pricing, while efficient in the sense that it clears electricity markets, can still lead to a reduction in profits and therefore investment. First, by raising the average electricity price (because shortages are positive on average) and therefore raising the marginal cost of plants. Under decreasing returns to scale, this marginal cost increase should lead to plants contracting. Furthermore, as Johnston (2018) shows, electricity price volatility can also induce reductions in investment due to uncertainty-induced "wait-and-see" effects. Despite these potential pitfalls, electricity price shocks should be quantitatively less important than shortage shocks ex-ante. For example, a 10% shortage (adjusted for λ) would lead to a 13.16% (15.51%) reduction in profits for plants without generators in Maharashtra (Punjab). In contrast, the equivalent dynamic electricity price increases of 9.10% and 7.90% would only reduce profits by 0.90% and 2.07% in Maharashtra and Punjab, respectively. This large difference in magnitude is primarily driven by the low share of electricity as a component of plants' production costs, and suggests that electricity price shocks should have a far smaller impact than shortage shocks.

This difference is reflected in Table 7.2, which provides a comparison of the dynamic pricing regime to the status quo shortage regime (relative to a base economy with $\lambda = 0$ for both states).

In terms of both value added and producer surplus, the negative consequences of dynamic pricing are far more modest than those of shortages, implying long-run costs about 1/10 (1/5) of the size of those under the shortage regimes in Maharashtra (Punjab). Furthermore, though electricity prices are higher, they are never high enough to incentivize generator adoption to substitute self-generated electricity for the grid in either state. The effects on investment behavior are modest as well, with a reduction of 0.6 and 1.7 p.p. for Maharashtra and Punjab. This finding implies electricity price volatility due to the dynamic pricing policy is not large enough to induce reductions in investment by plants.

The main implication of this counterfactual analysis is that dynamic pricing can substan-

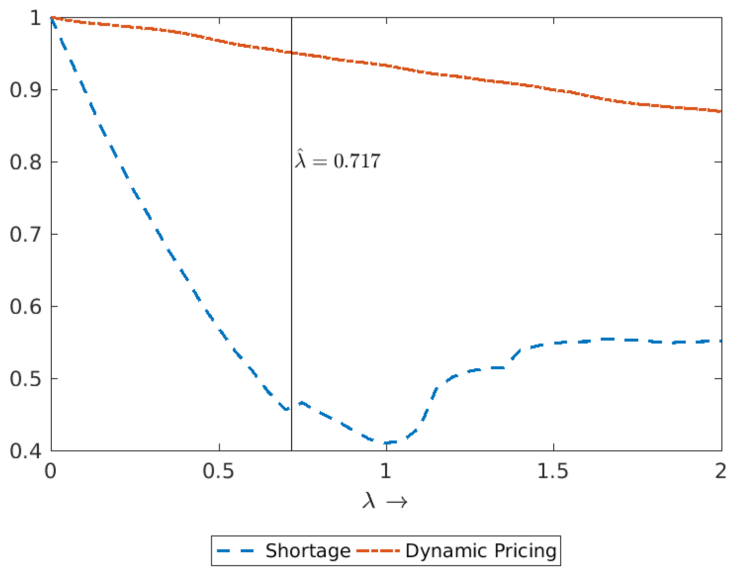
Table 7.2: Counterfactual Outcomes under Dynamic Pricing

	Shortage	Dynamic Pricing
Panel A. Maharashtra		
Δ Value Added (%)	-52.27	-4.956
Δ Producer Surplus (%)	-43.59	-4.032
Δ Mean Investment Rate (p.p.)	-7.089	-0.639
Δ Generator Ownership Rate (p.p.)	+11.84	0
Panel B. Punjab		
Δ Value Added (%)	-63.64	-13.46
Δ Producer Surplus (%)	-57.12	-11.45
Δ Mean Investment Rate (p.p.)	-11.01	-2.251
Δ Generation Ownership Rate	+39.77	0

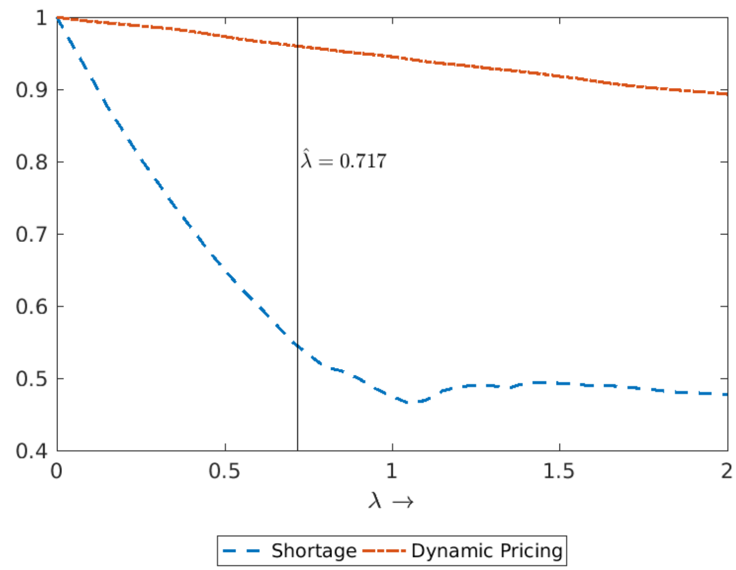
Reports the change in value added, producer surplus, investment moments and generator ownership for Maharashtra and Punjab. All variables are reported as changes (units in parentheses) relative to the stylized economy with no shortages at constant baseline electricity prices.

tially alleviate the burden of shortages on manufacturers. As further evidenced in Figures 7.5 and 7.6 (which compare the shortage and dynamic pricing regimes for various levels of λ), the implied value added and producer surplus losses from dynamic pricing are substantially lower than from shortages. Therefore, despite the many cost-side factors that affect the marginal cost of electricity supply, relaxing price rigidities and allowing electricity prices to clear markets can lead to considerably lower losses than those from fixed tariffs with shortages.

Figure 7.5: Shortage versus Dynamic Pricing Regime: Maharashtra

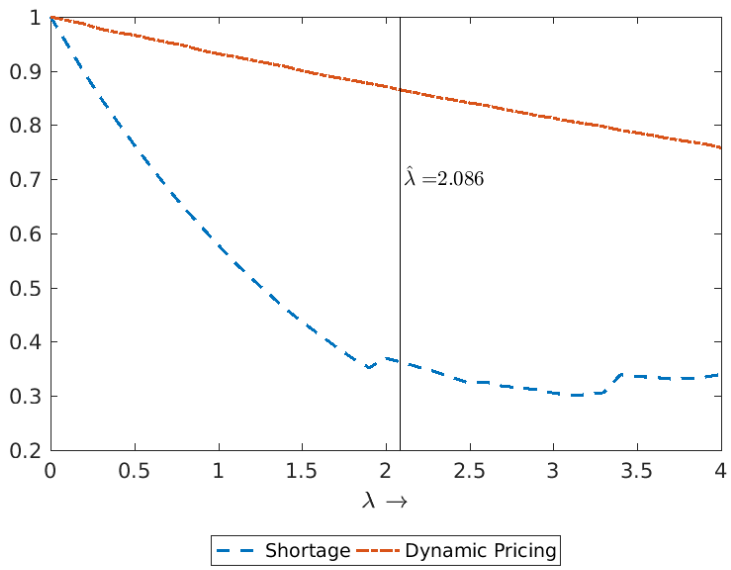


(a) Value Added

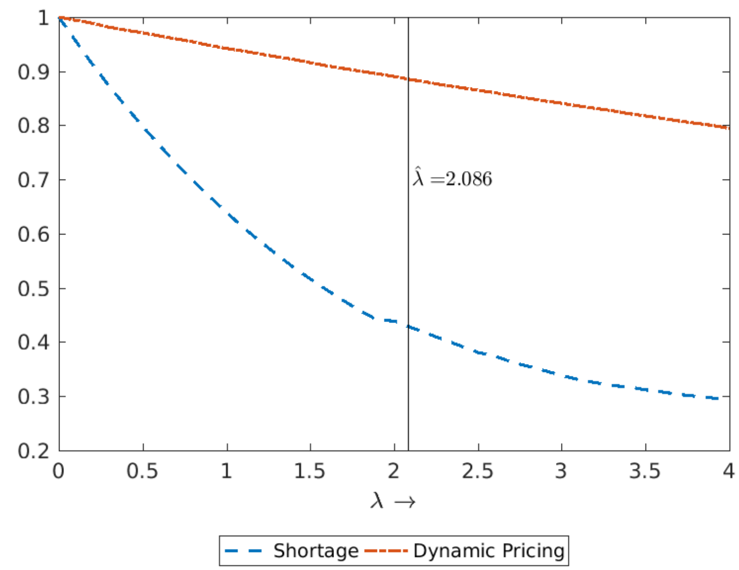


(b) Producer Surplus

Figure 7.6: Shortage versus Dynamic Pricing Regime: Punjab



(a) Value Added



(b) Producer Surplus

While the improvement under dynamic pricing is large in magnitude, the direction is intuitive and policymakers in India have indeed discussed tariff increases and reforms at various points in time. However, due to the political pressures discussed in chapter 2, the pricing structure of electricity markets has been slow to change. Furthermore, the implementation of dynamic pricing faces infrastructure barriers, particularly from inadequate metering and billing practices. Nevertheless, the counterfactual analysis of dynamic pricing suggests that the benefits are quantitatively large and important enough to justify the costs of implementation.

7.3 Effects of Shortage Uncertainty

In the presence of fixed investment costs with the option to not invest, uncertainty about future states has been shown to lead to "wait-and-see"-type effects where firms delay their investments (see, for example, Bloom et al., 2007). However, how uncertainty would impact investment behavior when agents have access to an insurance margin, such as generators for shortage shocks, is unclear. As the effects of uncertainty in the presence of endogenous insurance has received little attention, an examination of what responses uncertainty in shortages would induce in firm behavior is worthwhile.

Shortage uncertainty in this setting refers to the conditional volatility σ_B of the shortage shocks. Notably, an increase in σ_B while holding the mean μ_B constant places greater weight on more extreme (very low and very high) shortage levels. As such, the effects of an increase in σ_B are ambiguous. Given the costs of self-generation, plants should be more willing to respond to extreme changes in the shortage state than for less extreme ones but whether they would respond more to low shortage states (by delaying generator adoption) or to high shortage states (by increasing adoption and delaying removal) is unclear. The interactions between productive investment and generator ownership add to this ambiguity, with the answer being an empirical one determined by the costs along both margins. Hence, I conduct the following counterfactual analyses to study the implications of shortage uncertainty.

First, I compare output and investment outcomes from the estimated model to counterfactual economies with a constant shortage and no uncertainty, that is, setting $\sigma_B = 0$ while holding μ_B constant. Examining these outcomes (Table 7.3) reveals that value added and producer surplus are lower when $\sigma_B = 0$ than under the status quo.

Table 7.3: Counterfactual Outcomes under no Uncertainty

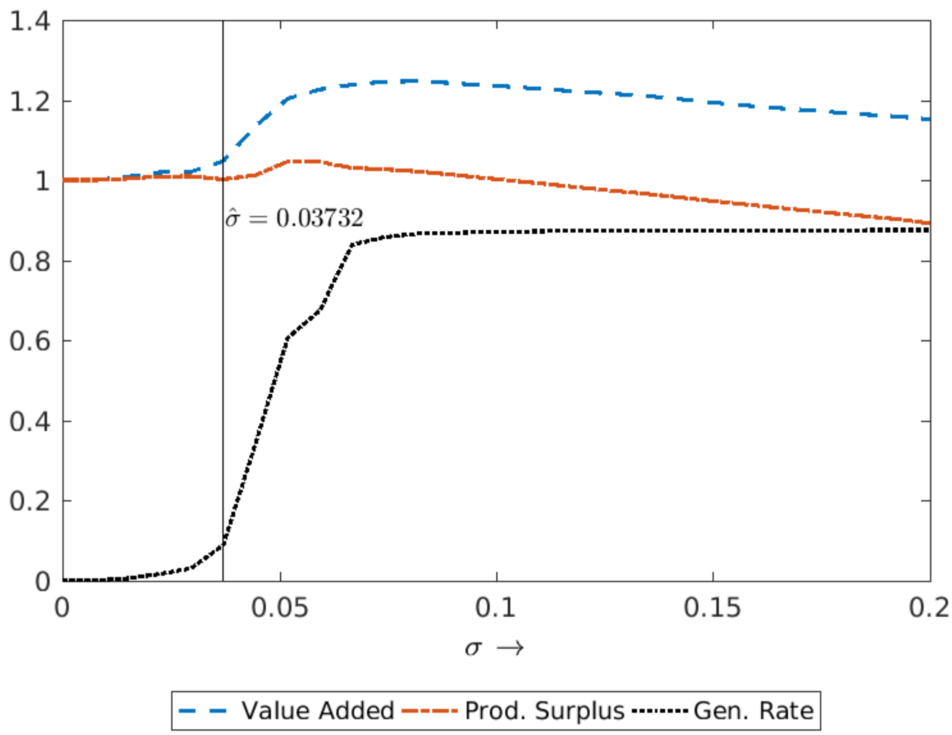
	Maharashtra	Punjab
Δ Value Added (%)	-4.783	-21.52
Δ Producer Surplus (%)	-0.207	-7.796
Δ Mean Investment Rate (p.p.)	-0.243	-1.327
Generator Ownership Rate (p.p.)	0	0.867
Δ Generator Ownership Rate (p.p.)	-11.84	-38.90

Reports the change in value added, producer surplus, investment moments as well as generator ownership level and difference for Maharashtra and Punjab when $\sigma_B = 0$. Differences are relative to the estimated model.

Although the effects for Maharashtra are modest (-4.78% and -0.207%), the implied changes for Punjab are very large at -21.52% and -7.80%. This perhaps surprising result can be rationalized by the fact that higher σ_B places more weight on low shortage states, which benefits plants. Additionally, the convexity of the profit losses induced by shortages (equations (5.11) and (5.13)) imply that the marginal profit loss of shortages is actually decreasing. Therefore, the increased weight on worse shortage states due to higher σ_B doesn't completely counteract the accompanying higher weight on better shortage states. However, further examination of this result reveals that this high levels of uncertainty can still have adverse effects.

Figures 7.7 and 7.8 plot the changes in value added, producer surplus and generator ownership as a function of σ_B (relative to when $\sigma_B = 0$ for value added and producer surplus). Interestingly, an increase in value added is observed for initial increases in σ_B whereas the changes in producer surplus are much more moderate. However, as shortage uncertainty increases to high levels, plants face more extreme high shortage states, resulting in greater generator adoption and reduced producer surplus. Output, however, remains high due to plants having a distorted incentive to stay large to exploit the economies of scale in generator ownership. Notably, generator adoption is very low for $\sigma_B = 0$ in both Maharashtra and Punjab, suggesting shortage uncertainty could indeed be an additional driver of generator ownership beyond just the average shortage. Examining the investment response further reveals how plants using the generator margin can undo the 'wait-and-see" effects of shortage uncertainty, though at a cost to their welfare.

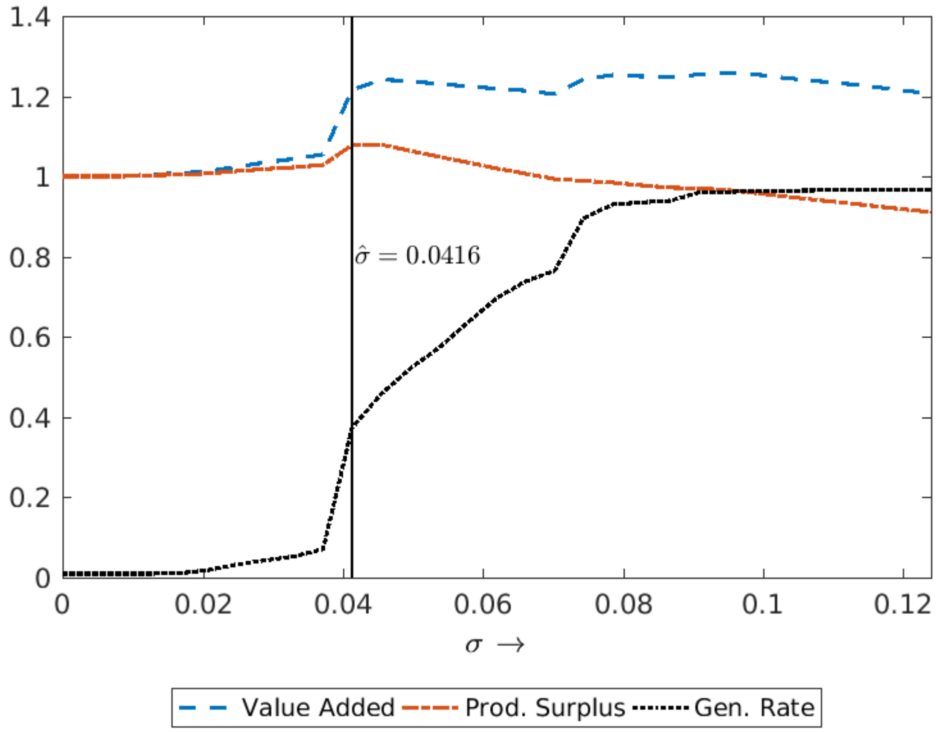
Figure 7.7: Change in Value Added, Producer Surplus and Generator Adoption with σ_B: Maharashtra



Plots the changes in value added and producer surplus (relative to $\sigma_B = 0$) and the generator ownership as functions of σ_B for Maharashtra.

Conforming to the common view that greater uncertainty leads to greater inaction, investment inaction rates initially increase (Figures 7.9 and 7.10 for Maharashtra and Punjab, respectively) for moderate increases in σ_B from 0. However, as shortage uncertainty rises

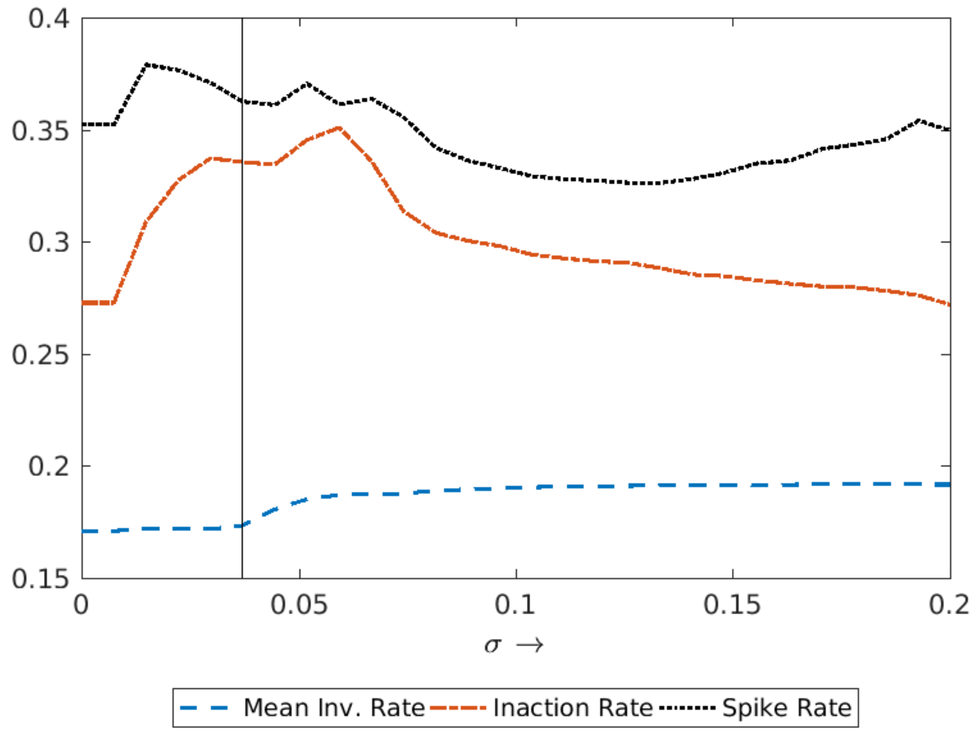
Figure 7.8: Change in Value Added, Producer Surplus and Generator Adoption with σ_B: Punjab



Plots the changes in value added and producer surplus (relative to $\sigma_B = 0$) and the generator ownership as functions of σ_B for Maharashtra.

even further, plants increasingly adopt generators, causing a decline in investment inaction as plants are less exposed to shortage uncertainty once they begin to self-generate. To reiterate, the comparative static holds the average shortage constant, implying the effects of uncertainty could be non-monotonic in the presence of endogenous insurance.

Figure 7.9: Change in Investment Behavior with σ_B: Maharashtra

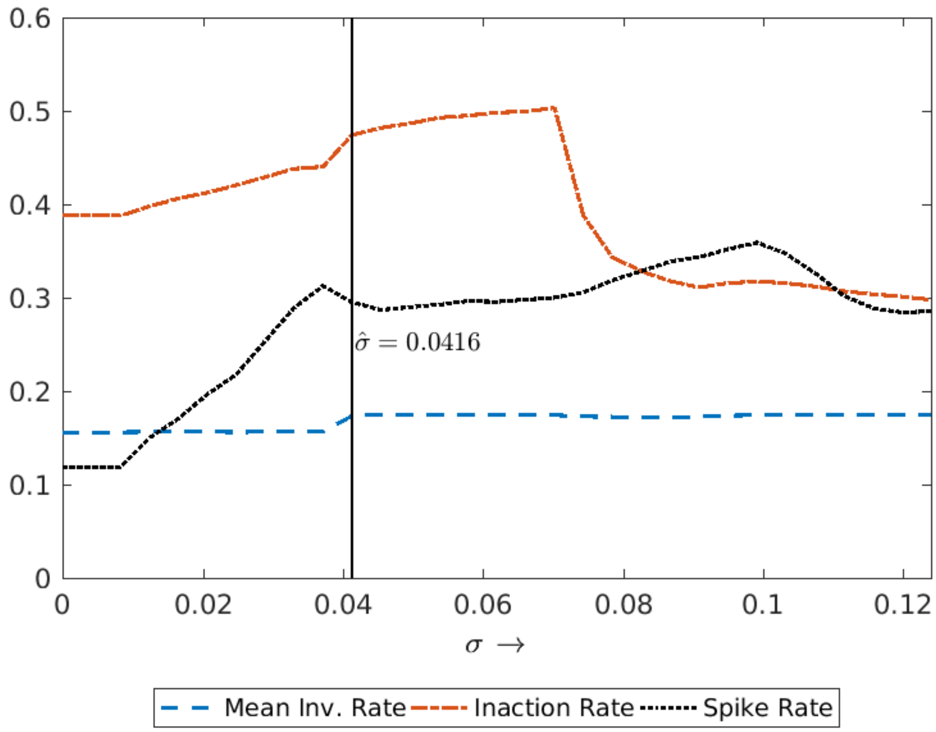


Plots the changes in the mean investment rate, investment inaction and spike rates as functions of σ_B for Maharashtra.

The aforementioned results are not necessarily generalizable to all models of uncertainty given the specific nature of the shortage shocks and cost structure of generator insurance. Nevertheless, they highlight that the underlying source of uncertainty as well as the possible endogenous insurance responses by agents can be highly important in certain settings.[2]

2. For example, Handley and Limão (2017) and Handley and Limao (2015) show how preferential trade agreements can undo the effects of trade policy uncertainty.

Figure 7.10: Change in Investment Behavior with σ_B: Punjab



Plots the changes in the mean investment rate, investment inaction and spike rates as functions of σ_B for Punjab.

CHAPTER 8

CONCLUSION

To conclude, the aim of this research was to study the potential long-run output and welfare costs of electricity shortages by examining the dynamic responses of Indian manufacturers. Specifically, I focus on the responses along investment in productive capital and generator adoption margins.

I use a merged panel of state-level shortage data and plant-level microdata to show that electricity shortages are negatively correlated with plant investment on average. Furthermore, this relationship is quantitatively much weaker for plants with generators. Additionally, I find that, on average, plants invest less during spells of generator ownership than without, suggesting generators reduce profitability and therefore the returns to investment. I also find evidence that shortages reduce profits by reducing the capacity utilization of plants, supporting the results in Allcott et al. (2016).

I rationalize the above descriptive findings using a dynamic model of investment with productivity and electricity shocks along with generator adoption. I include a rich specification of capital adjustment frictions and generator costs to match the investment behavior of Indian manufacturers and the interaction between generator and productive capital. I then estimate the model for two states - Maharashtra and Punjab - using Simulated Method of Moments to quantify the long-run costs of electricity shortages.

I find that the long-run effects are substantially larger than the short-run effects: In the long-run, value added and producer surplus are lower by 52.27% and 43.59% in Maharashtra, while they are 63.64% and 57.12% lower in Punjab, respectively. I find that dynamics are important, as the long-run costs are approximately 2.5-3.5 times as large as the short-run costs. Although generator adoption ameliorates the negative value added effects, producer surplus is still lowered due to the costs of generator adoption and maintenance.

I then conduct a dynamic-pricing-policy exercise that suggests the benefits of relaxing electricity price rigidities to clear electricity markets and prevent shortages are quantitatively large. Under dynamic pricing, the value added and producer welfare losses amount to 4.96% and 4.03% in Maharashtra (approximately 1/10 of the shortage losses), while they amount to 13.46% and 11.45% in Punjab (approximately 1/5). Despite the challenges of implementing such a policy, my results imply the benefits of adopting dynamic pricing are substantial.

Finally, I also study the effects of shortage uncertainty. I find that shortage uncertainty alone increases value added and producer surplus at the estimated levels. This finding is explained by the facts that more shortage uncertainty places greater weight on better shortage state and that the marginal effect of shortages on profits is diminishing. However, this effect is non-monotonic, because very high levels of shortage uncertainty lead to plants adopting generators as a response to extreme high shortage states. Consequently, plants have a distorted incentive to stay large to exploit economies of scale in generator ownership, particularly given the partial irreversibility of generator adoption. Therefore, high levels of shortage uncertainty lead to higher value added but lower producer surplus.

The first key takeaway is that dynamics can be very important. Producers can form expectations about future electricity supply (or other economic) conditions and respond dynamically, causing long-run impacts that differ substantially from short-run ones. Therefore, dynamic margins merit consideration and further exploration. The second is that electricity pricing is a powerful policy instrument that has been potentially under-utilized in settings with reliability problems, like India. The third additional conclusion, highlighted by the analysis of shortage uncertainty, is that the nature of the economic shock matters along with the natural responses available to producers. In the context of electricity shortage shocks and the natural response of backup generator adoption as insurance, the typical delaying effects of uncertainty on investment don't always hold. Altogether, this work contributes in providing a flexible framework to quantify the true economic costs of unreliable electricity, an idea of the mechanisms that drive these costs as well as a policy response that can help to substantially mitigate them, with the aim of helping countries overcome this barrier to their growth.

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APPENDIX A

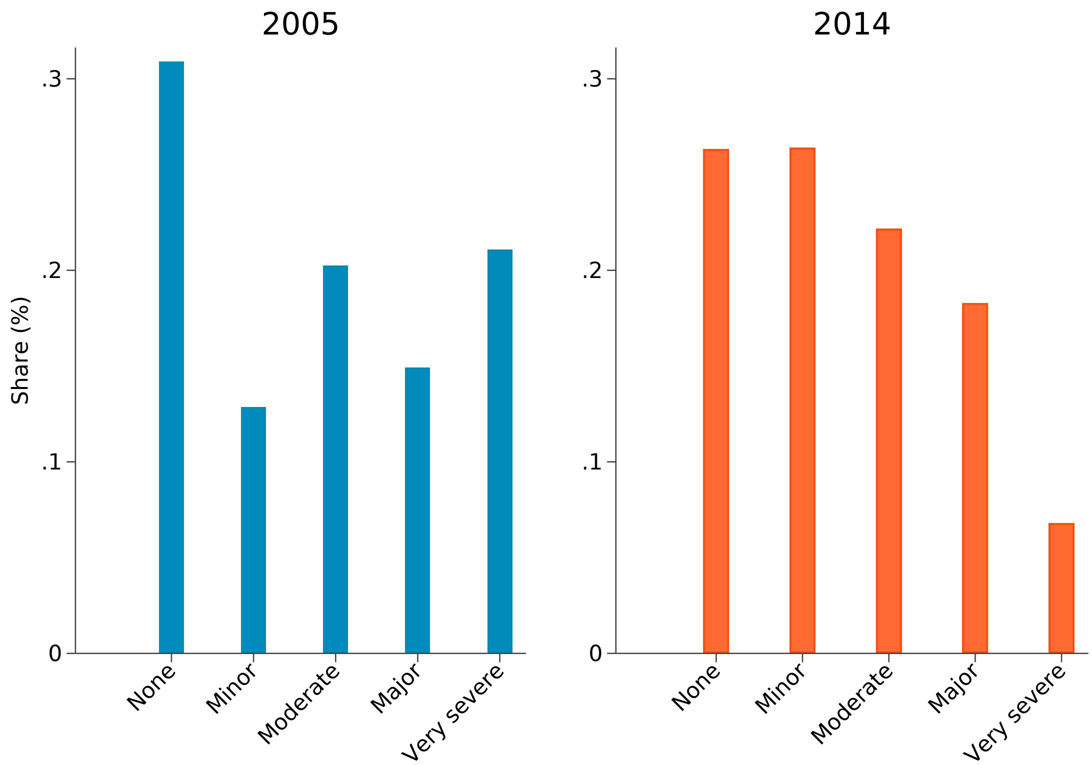
WORLD BANK ENTERPRISE SURVEY OBSTACLES

Table A.1: Biggest Obstacle to Operation of Establishment: 2005 and 2014

Obstacle	Frequency (%)
Panel A. WBES 2005	
Electricity	33.54
High Taxes/Tax Administration	23.95
Corruption	10.20
Labor Regulations/Skills	8.09
Access/Cost of Credit	6.08
Other	18.14
Panel B. WBES 2014	
Corruption	20.57
Electricity	15.15
Tax Rates	14.61
Access to Finance	10.24
Informal Competitor Practices	9.18
Labor Regulations	6.39
Other	23.86

Reports the frequency of responses of the biggest obstacles to operation and growth from the World Bank Enterprise Survey 2005 (Panel A) and 2014 (Panel B). Obstacles reported in order of frequency (high-to-low), smallest obstacles aggregated and reported under "Other". Based on 2,138 responses in 2005 and 8,766 responses in 2014.

Figure A.1: Severity of Electricity as an Obstacle to Operation: 2005 and 2014



Reported degrees to which electricity is an obstacle to operations from the World Bank Enterprise Survey for the years 2005 and 2014. Bars report percentages for each response, based off 2,278 responses in 2005 and 9,276 responses in 2014.

APPENDIX B

DATA AND SAMPLE SELECTION

In this appendix, I describe the sample selection process and provide additional information about the ASI data.

B.1 Selection of Baseline Sample

The full ASI sample for the period 1998-99 to 2012-13 consists of 746,968 plant-year level observations. A small number of establishments that appear multiple times within the same year with inconsistent data across observations are dropped, leaving 746,926 unique plant-year cells. I then drop 40,552 observations that are listed under non-manufacturing sectors. Some sampled plants are reported to be closed or unresponsive - these 162,784 observations are also removed.

The Ministry of Statistics and Programme Implementation (MOSPI) uses the National Industrial Classification system (NIC) to categorize industries. The NIC codes are similar to industrial classifications in other countries, such as the SIC and NAICS codes used in the United States. The NIC codes were revised twice within my sample period, in 2004 and 2008. I convert all NIC codes to the 2004 system using concordance tables provided by MOSPI; these conversions are made at the 4-digit level (the level at which the concordance tables are provided), with the 5-digit level being the finest level of disaggregation. For the purposes of this study, I refer to an NIC 4-digit code as an industry, since 5-digit codes are inconsistent over time. I drop those establishments that are classified under non-manufacturing NIC codes, a total of 40,552, restricting the sample to the manufacturing sector.

I deflate revenues using industry specific deflators from the "Wholesale Price Index" (WPI) series compiled by the Office of the Economic Adviser in India. Since the WPI classifications do not perfectly match NIC (although this was the case for older versions), I match commodity classifications in the WPI to 2-digit NIC codes and deflate at the two digit level. I also use specific deflators for coal, fuels and electricity from their counterparts in the WPI series. To deflate material expenditures, I use the Input-Output table from 2008, compiled by the Central Statistical Office (CSO). The input-output tables use yet another different classification of industries, which I match to the NIC at the 2-digit level. For each 2-digit industry, I compute the share of all other industries in its input bundle and use these shares as weights to construct a materials deflator as the input share-weighted sum of industry-specific output deflators. I deflate labor expenditures using the CPI series (downloaded from the Reserve Bank of India's website). Finally, for capital expenditures, I use investment deflators provided by the Reserve Bank of India (RBI). All quantities are deflated to 2004 levels.

Although some plants are retroactively identified to be geographically in the state of Telangana, the state itself was only formed in 2014 by splitting off from the state of Andhra Pradesh. Therefore, for consistency, I redefine their location as Andhra Pradesh. Except for Delhi, I drop all plants located in union territories that are governed by the Central Government of India - these include all plants located in Pondicherry (4,993), Daman & Diu (6,596) as well as Dadra & Nagar Haveli (5,747). I also drop all plants from Sikkim (188 observations), since Sikkim was only included in the ASI sampling for the later years. I exclude a small number plants from the island states - Andaman & Nicobar Islands and Lakshadweep (164 observations between both) - since these states are economically small and isolated from the mainland. Finally, I exclude plants from Goa (4,822 observations) since it too is a small state with a small industrial sector, and plants from Jammu & Kashmir (4,399 observations) due to the sensitive politics of the region. This step leaves a total of 516,681 observations.

Next, I drop the 68,675 observations that are missing revenues. I then remove observations based on their inputs. I drop observations for which total (real) labor income is missing or, as a share of real revenues, is greater than 2. Similarly, I also drop those observations for which real material and electricity costs are missing, or as revenue shares are greater than 2.5

and 1, respectively. I also drop those plants that show implausibly large year-to-year changes in employment. Specifically, I remove those plants whose employment changes by more than a factor of 4 per year with a total employment of greater than 2,000 employees. Then, I drop those observations for which the the capital stock is missing or the revenue share of the rental value of capital is greater than 2. I compute the rental rate of capital as the sum of the real interest rate and a 15% depreciation rate. Finally, I drop those observations for which a perpetual inventory calculation of the capital stock yields negative values. I also drop a very small number of observations in industries with fewer than 50 total observations, leaving a sample size of 409,655. Finally, I drop 4,016 observations that report zero electricity, leading to the final baseline sample of 405,639 observations.

B.2 Variable Sample Selection

I make use of certain variables in my analysis that are not available for all firms, including the investment rate, investment in non-equipment capital, reported depreciation and working day variables. For all statistics and results reported using these variables, I make use of the subset of the baseline sample for which they're available. To ensure robustness to outliers in these variables (since I don't clean on them), I winsorize both the investment and depreciation rates at the first and ninety-ninth percentile, excluding outliers from the regression analyses.

APPENDIX C

ADDITIONAL RESULTS

C.1 Robustness Regressions

Table C.1: Grid electricity and self-generation variation with the Shortage variable: with state-specific linear trends

	(1)	(2)	(3)	(4)
	log(Grid Elec.)	log(Grid Elec.)	log(Gen. Elec.)	Gen. Share
Shortage	-0.742***		3.332***	0.115***
	(0.0946)		(0.349)	(0.0263)
1(Gen. = 0) × Shortage		-0.749***		
		(0.0989)		
1(Gen. = 1) × Shortage		-0.728***		
		(0.101)		
Observations	333,057	333,057	116,275	333,057
R-squared	0.946	0.946	0.840	0.649
Plant FE	Yes	Yes	Yes	Yes
NIC4 x Year FE	Yes	Yes	Yes	Yes
State Linear Trend	Yes	Yes	Yes	Yes

Standard errors adjusted for two-way clustering on plant and state-year. *** p<0.01, ** p<0.05, * p<0.1.

Table C.2: Grid electricity and self-generation variation with the Shortage variable: using log(Availability) instead of shortage measure.

	(1) log(Grid Elec.)	(2) log(Grid Elec.)	(3) log(Gen. Elec.)	(4) Gen. Share
log(Avail.)	0.222***		0.156	-0.0410***
	(0.0519)		(0.248)	(0.0117)
1(Gen. = 0) × log(Avail.)		0.223***		
		(0.0520)		
1(Gen. = 1) × log(Avail.)		0.225***		
		(0.0520)		
Observations	333,057	333,057	116,275	333,057
R-squared	0.946	0.946	0.836	0.647
Plant FE	Yes	Yes	Yes	Yes
NIC4 x Year FE	Yes	Yes	Yes	Yes

Standard errors adjusted for two-way clustering on plant and state-year. *** p<0.01, ** p<0.05, * p<0.1.

Table C.3: Investment Relationship with Shortages and Generators: State Linear Time Trends

	(1) I/K	(2) $\log(I)$	(3) $\log(I_{neq})$
$1(\text{Gen.} = 0) \times$ Shortage	-0.120**	-0.480***	-0.410
	(0.0574)	(0.184)	(0.252)
$1(\text{Gen.} = 1) \times$ Shortage	-0.0758	-0.139	0.0325
	(0.0634)	(0.218)	(0.273)
$1(\text{Gen}_{it} = 1 \vert \text{Gen}_{i,t-1} = 1)$	-0.0284***	-0.0452**	-0.0576**
	(0.00548)	(0.0184)	(0.0251)
$1(\text{Gen}_{it} = 1 \vert \text{Gen}_{i,t-1} = 0)$	-0.00846	0.0294	-0.0229
	(0.00718)	(0.0227)	(0.0288)
$1(\text{Gen}_{it} = 0 \vert \text{Gen}_{i,t-1} = 1)$	0.0134**	0.0497**	0.0247
	(0.00596)	(0.0197)	(0.0266)
Observations	325,611	244,828	160,906
R-squared	0.419	0.744	0.702
Plant FE	Yes	Yes	Yes
NIC4 x Year FE	Yes	Yes	Yes
State Linear Trend	Yes	Yes	Yes

Dependent variables in specifications (1), (2) and (3) are the investment rate, log of investment expenditures and log of investment expenditures on non-equipment capital. Includes state linear time trends. Standard errors adjusted for two-way clustering on plant and state-year. *** p<0.01, ** p<0.05, * p<0.1.

Table C.4: Investment Relationship with Shortages and Generators: Robustness to Financial Development

	(1) I/K	(2) $\log(I)$	(3) $\log(I_{neq})$
$1(\text{Gen.} = 0) \times$ Shortage	-0.118**	-0.483***	-0.420*
	(0.0573)	(0.182)	(0.249)
$1(\text{Gen.} = 1) \times$ Shortage	-0.0687	-0.106	0.0494
	(0.0625)	(0.215)	(0.270)
$1(\text{Gen}_{it} = 1 \mid \text{Gen}_{i,t-1} = 1)$	-0.0286***	-0.0466**	-0.0585**
	(0.00549)	(0.0185)	(0.0251)
$1(\text{Gen}_{it} = 1 \mid \text{Gen}_{i,t-1} = 0)$	-0.00872	0.0271	-0.0247
	(0.00719)	(0.0227)	(0.0289)
$1(\text{Gen}_{it} = 0 \mid \text{Gen}_{i,t-1} = 1)$	0.0133**	0.0490**	0.0239
	(0.00595)	(0.0197)	(0.0266)
Observations	325,611	244,828	160,906
R-squared	0.419	0.745	0.702
Plant FE	Yes	Yes	Yes
NIC4 x Year FE	Yes	Yes	Yes
State linear trend	Yes	Yes	Yes

Dependent variables in specifications (1), (2) and (3) are the investment rate, log of investment expenditures and log of investment expenditures on non-equipment capital. Includes state linear time trends and value added of financial sector per capita. Standard errors adjusted for two-way clustering on plant and state-year. *** p<0.01, ** p<0.05, * p<0.1.

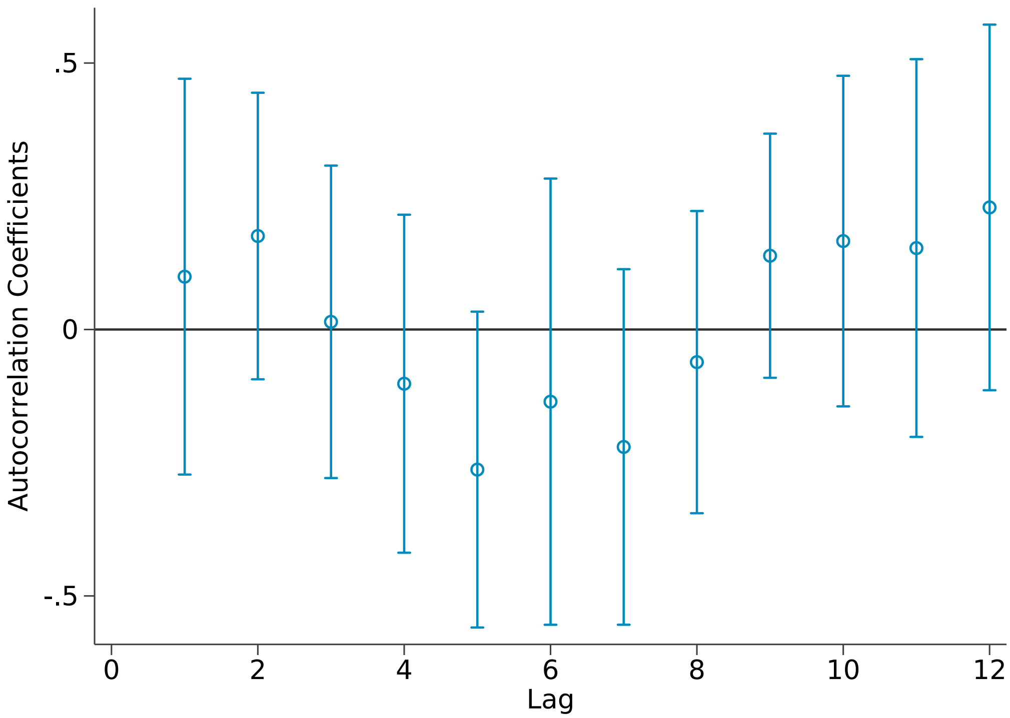
Table C.5: Depreciation and Shortages

	(1)
1(Gen. = 0) × Shortage	-0.0270***
	(0.00788)
1(Gen. = 1) × Shortage	-0.0151
	(0.00937)
Observations	325,758
R-squared	0.602
Plant FE	Yes
NIC4 x Year FE	Yes

Dependent variable in this table is the depreciation rate, defined as reported depreciation divided by the opening capital stock. Omitted controls include log(GSDP per capita), log(Population), log(Age) and log(Electricity Price). Standard errors adjusted for two-way clustering on plant and state-year. *** p<0.01, ** p<0.05, * p<0.1.

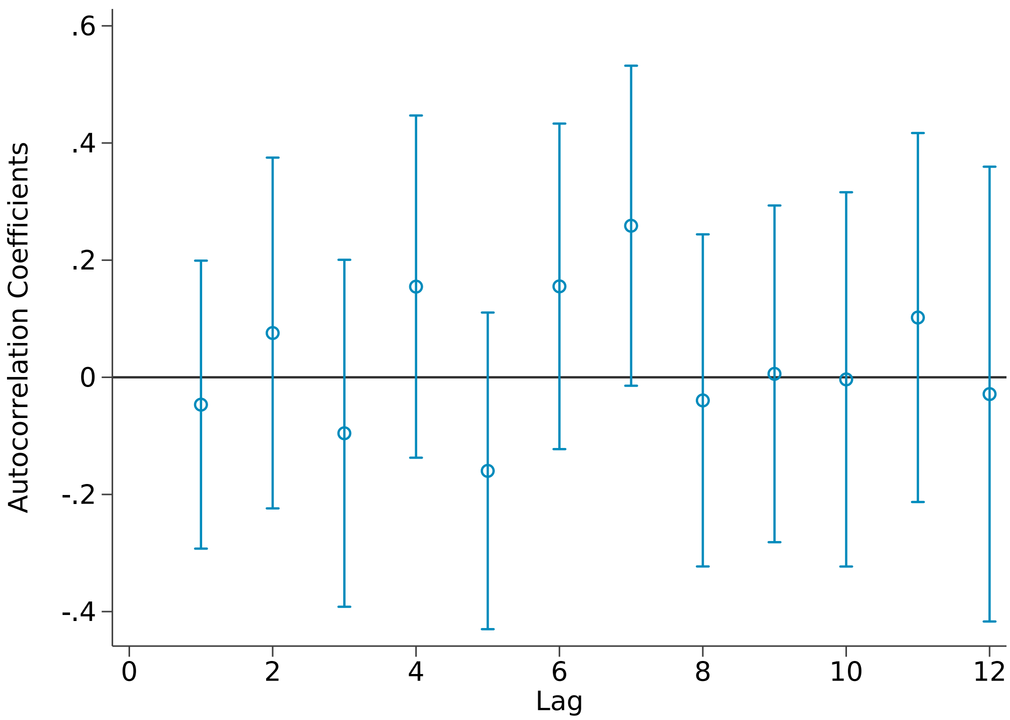
C.2 AR(1) Fit for Shortage Process

Figure C.1: Residual Autocorrelations for Maharashtra



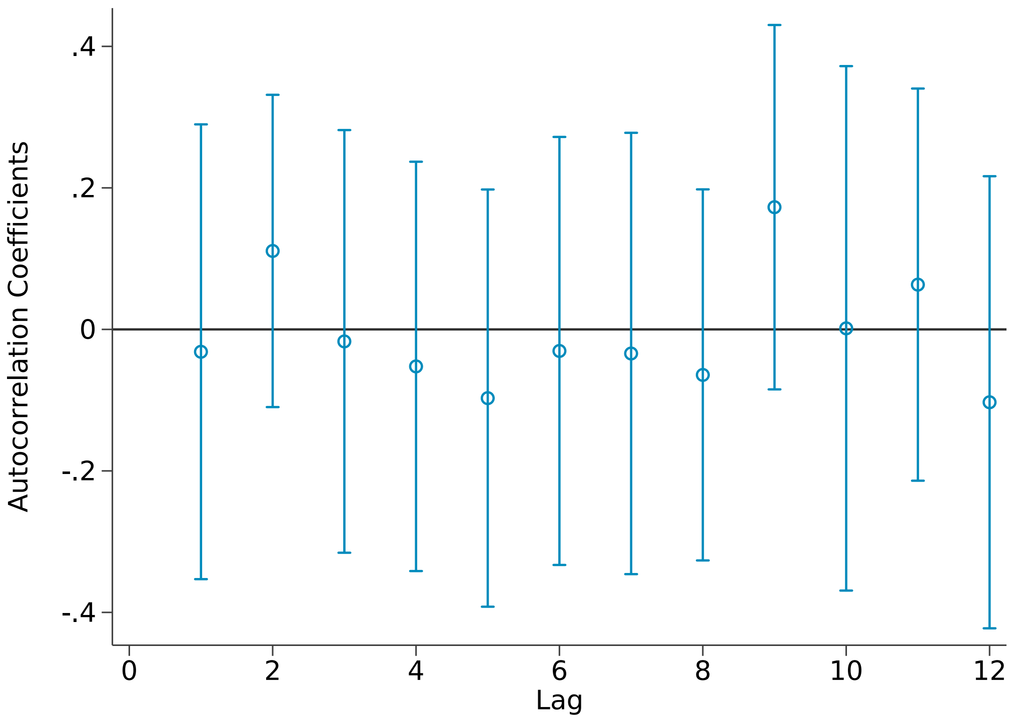
Plots autocorrelation coefficients along with 95% confidence intervals for estimated residuals after fitting AR(1) model to the monthly shortage process for Maharashtra.

Figure C.2: Residual Autocorrelations for Punjab



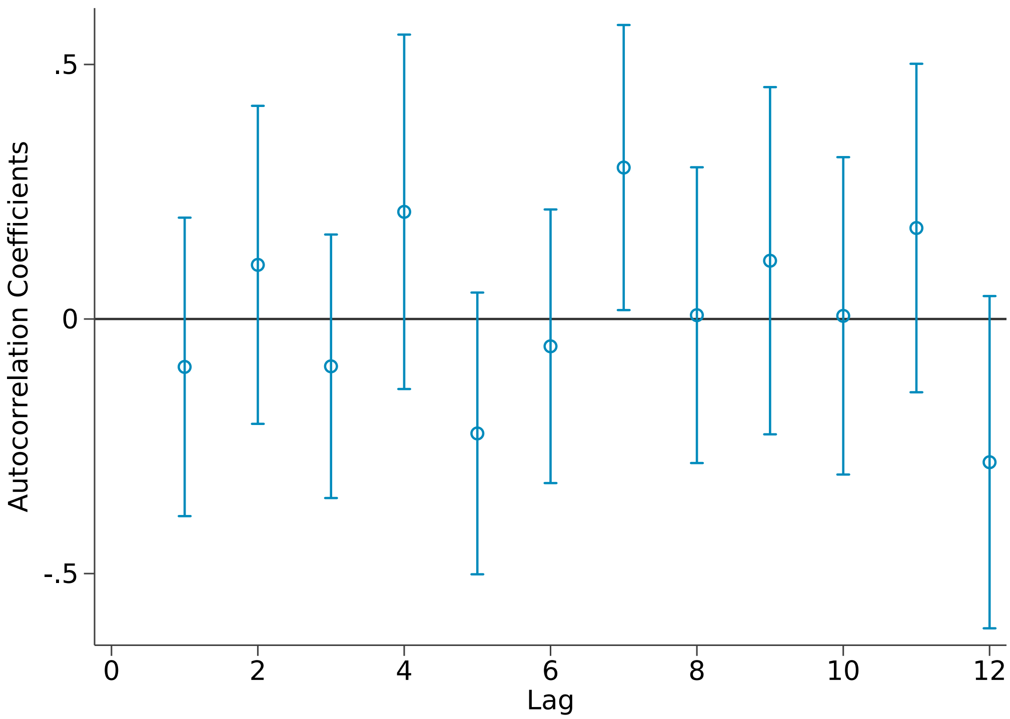
Plots autocorrelation coefficients along with 95% confidence intervals for estimated residuals after fitting AR(1) model to the monthly shortage process for Punjab.

Figure C.3: Residual Autocorrelations for Maharashtra with Seasonality



Plots autocorrelation coefficients along with 95% confidence intervals for estimated residuals after fitting AR(1) model with seasonality (month fixed effects) to the monthly shortage process for Maharashtra.

Figure C.4: Residual Autocorrelations for Punjab with Seasonality



Plots autocorrelation coefficients along with 95% confidence intervals for estimated residuals after fitting AR(1) model with seasonality (month fixed effects) to the monthly shortage process for Punjab.