

HARVARD UNIVERSITY
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The undersigned, appointed by the
Department of Public Policy
have examined a dissertation entitled

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presented by Shefali Khanna

candidate for the degree of Doctor of Philosophy and hereby
certify that it is worthy of acceptance.

Signature [Handwritten Signature]

Typed name: Professor Rema Hanna, Chair

Signature [Handwritten Signature]

Typed name: Professor Robert Stavins

Signature [Handwritten Signature]

Typed name: Professor Jie Bai

Signature [Handwritten Signature]

Typed name: Professor Christopher Knittel

Date: April 20, 2021

Essays in Energy and Development Economics

A dissertation presented
by

Shefali Khanna

to

The Department of Public Policy

in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy
in the subject of
Public Policy

Harvard University
Cambridge, Massachusetts
April 2021

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Dissertation Advisors:

Professor Rema Hanna
Professor Robert Stavins

Author:

Shefali Khanna

Essays in Energy and Development Economics

Abstract

This dissertation studies topics in environmental and energy economics with a focus on developing countries. Combining detailed billing and outages records with original survey data, the first two chapters shed light on how residential, informal settlement, commercial and industrial customers in urban India respond to retail electricity prices, how they value electricity reliability and the implications for efficient retail pricing. The third chapter focuses on how the absence of centralized and dynamic wholesale electricity markets affects the relative performance of market-based environmental policies.

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PREVIEW

Acknowledgments

I am grateful for generous support from the Harvard Climate Change Solutions Fund, the International Growth Centre, the Belfer Center for Science and International Affairs at Harvard Kennedy School, the Joseph Crump Fellowship from the Mossavar-Rahmani Center for Business and Government at Harvard Kennedy School, and the South Asia Institute at Harvard University.

I am indebted to Rema Hanna, Jie Bai, Robert Stavins and Christopher Knittel for their constant support and encouragement. Their mentorship has been immensely valuable and I am incredibly privileged to have had them as advisors. I also thank Joseph Aldy, Shawn Cole, Kelsey Jack, Namrata Kala, Gabriel Kreindler, Rohini Pande and members of the Harvard and MIT faculty for helpful conversations. I thank Marcos Barrozo, Megan Bailey, Tridevi Chakma, Todd Gerarden, Will Rafey, Daniel Velez-Lopez and other participants of the Harvard Environmental Economics Lunch for their thoughtful comments and critiques of my projects.

I am grateful to Neeraj Tridevi, Aastha Jain, Sanghamitra Thakur, Vidushi Dhawan, Aparna Bhau-mik and the Evidence for Policy Design (EPoD) India team as well as Mohammad Ashraful Haque, Zannatul Akhand, Avinno Faruk, Elizabeth Friesen, Sneha Subramanian and the Innovations for Poverty Action (IPA) Bangladesh team for excellent research assistance. I thank Praveer Sinha, CEO & Managing Director, Tata Power, and his team for providing access to billing and outage records of customers of Tata Power Delhi Distribution Limited. I thank H.S. Bajwa, Executive Director (Coal), Railway Board, Ministry of Railways, Government of India and Ashish Sharma of the Centre for Railway Information Systems for their assistance in facilitating access to the Freight Operations Information Systems (FOIS) commercial database. In no particular order, I thank Sushanta Chatterjee, Arvinder Singh Bakshi, Geetu Joshi, S.C. Saxena, S.K. Soonee, Pankaj Batra, Somit Dasgupta, Karthik Ganesan, Kapardhi Bharadwaj, Ashwini Swain, Daljit Singh, Rahul Tongia, Puneet Kamboj, Ranjit Bharvirkar, Ranjit Deshmukh, Rohit Chandra, Shantanu Dixit, Debabrata Chattopadhyay, Phillip Hannam, Demetrios Papathanasiou, Hussain Samad, Alisha Pinto, Kaveri Iychettira, Michael Davidson, Henry Lee, Jevgenijs Steinbuks, Sandhya Sundararagavan, Shruti Mahajan, Puneet Chitkara and Suresh Nagarajan for conversations that contributed immensely to all three of the chapters in this dissertation.

I especially thank Kevin Rowe for his unwavering partnership as a coauthor as well as Blake Heller and Elizabeth Spink for their invaluable friendship and camaraderie. I am eternally grateful for having gained so much from so many incredible people at Harvard. And last, but not least, I thank my family for supporting me through the ups and downs of the last six years.

To my parents

PREVIEW

Introduction

The chapters of this dissertation bring robust evidence to bear on the discussion around electricity market reform in India, with lessons that are broadly applicable across the developing world.

In my Job Market Paper, Kevin Rowe and I study the short- and long-run responses of electricity consumption and bill payments to retail prices in Delhi, India from 2015 to 2019. Using billing data from one of Delhi's three private electricity distribution utilities, we reconstruct payment histories for more than 1.5 million informal settlement, residential, commercial, and small industrial customers. Pricing reforms beginning in 2014 introduced large notches in the marginal price schedule, which we use in a regression discontinuity framework to analyze the short-run response of customers to non-marginal increases in the average cost of electricity. We find that residential demand is very inelastic to electricity prices in the short run. Large but transient increases in arrears following the billing shocks suggest that non-payment may play a role in dampening the magnitude of these elasticities. In particular, customers appear to allow arrears to absorb a portion of their increased charges while modestly reducing their consumption in the months following a billing shock. We then turn to the long run, where we use an instrumental variable strategy that exploits a rounding rule in the electricity price schedule, which generates minute but sustained, plausibly-exogenous variation in average electricity prices. In the long run, both demand and non-payment are highly elastic to prices, though there is significant heterogeneity across the distribution of consumption levels. While reducing subsidies for poor consumers would come at significant cost in terms of reduced surplus for these consumers – who are also the most difficult to reach with other types of transfers – we also expect non-payment to rise in response to price increases, mitigating the improvements to utility finances these increases are intended to support. In contrast, commercial and industrial customers, who pay prices well above the average cost to the utility, are substantially more elastic to retail prices than residential customers. These large elasticities provide a strong rationale for reducing power prices for these customers. In addition to reducing a large distortion to consumption, the behavioral response to this policy would grow the industrial and commercial customer base.

In Chapter 2, we take advantage of features of the electricity distribution network that expose similar customers to plausibly exogenous annual variation in electricity reliability to evaluate residential consumers' consumption and appliance investment responses to power outages. Using original household survey data and four years of billing and power outage records for more than one million customers, we estimate that an additional hour per month of power outages reduced electricity consumption by 4.85 percent. We plan to combine these estimates with the demand elasticities to develop a revealed preference measure of the value of lost load (VoLL) – the amount per unit of electricity that customers would be willing to pay to avoid a disruption in their service – that is differentiated by season and customer type. VoLL is an important policy parameter used in the design of retail pricing and demand response programs among other applications.

Developing countries face a unique set of challenges in expanding electricity access and meeting

the rising demand for energy, while also attempting to decarbonize their economies. One such challenge is that competition in the most emissions-intensive commodity-based industries, such as electricity generation, is typically constrained as these sectors are often heavily regulated or nationalized. Chapter 3 asks how market-based environmental policies would perform in non-market-based energy systems or in the absence of centralized and dynamic wholesale electricity markets. Electricity in India is transacted primarily through long-term bilateral contracts between power plants and state-owned distribution companies. These contracts consist of a two-part tariff, a fixed and a variable charge, neither of which have any time-of-day component. As a result, the market design invariably generates short-run misallocation in dispatch and weakens the incentive to develop flexible power generation or storage to complement renewable capacity in the long run. I assemble a detailed country-wide dataset on coal plant operations, thermal efficiency, freight shipments from coal mines, delivered coal prices, and long-term power purchase contracts from 2012 until 2020. I examine the impact of statutory changes in domestic delivered coal prices on utilization rates of coal-fired power plants and find no overall effect. However, heterogeneity analysis reveals that the demand for electricity from coal-fired power plants with a higher share of capacity allocated under long-term bilateral contracts is less sensitive to changes in coal prices, implying that the existing market design could erode some of the benefits of carbon pricing.

Chapter 1

Short and Long-Run Consumption and Non-Payment Responses to Retail Electricity Prices in India ¹

1 Introduction

Throughout the world, many public utility companies providing services like electricity, water, transportation, and sanitation find themselves in a political-economic equilibrium characterized by poor service quality and poor financial performance. This equilibrium is perpetuated by a self-reinforcing cycle in which regulated prices set below cost deprive utility companies of the resources needed to maintain high levels of service quality. In turn, poor service quality undermines the value of these services to the public and the ability of policymakers to justify raising prices or maintaining high levels of support from general tax revenues. In some cases, widespread non-payment or outright theft of public services exacerbates this cycle.

For decades India's electricity distribution segment has struggled to rise from a deep infrastructure quality trap. As of 2019, the approximately 100 utility companies serving retail customers across the country collectively held about USD 56 billion in outstanding debt, equivalent to 1.9 percent of India's GDP ([ETEnergyWorld, 2020](#)). While many of these utilities have managed to improve service quality in recent years, grid capacity shortfalls and deferred maintenance mean that hundreds of millions of people likely experience more than 10 hours of power outages every day ([Aklin *et al.*, 2016](#)). In spite of deeply subsidized retail price schedules for residential and

¹Co-authored with Kevin Rowe

agricultural customers, these utilities have long faced extreme rates of non-payment and pilferage. In 2019 the utilities collected revenue on only about 77 percent of the kilowatt hours (kWh) they served to customers, with the gap reflecting a combination of technical grid losses, failures to bill customers, and non-payment of bills ([Power Finance Corporation Ltd., 2020](#)). For several utilities, these losses were as high as nearly 40 percent.

Recent research on this topic has pointed toward highly subsidized retail prices as a root cause of dysfunction in electricity distribution in settings like India ([McRae, 2015](#); [Burgess *et al.*, 2020](#)). The authors of both of these papers argue for dramatically reducing retail subsidies for electricity, which amount to 50 percent or more of the average cost of supplying power to customers served by many of India's utilities. Under these policy prescriptions, raising retail prices could increase welfare by eliminating distortions, improve the finances of electric utilities, and, as a result, support investment in better service quality. However, such reforms would also come at a cost, reducing affordability and exacerbating already high rates of non-payment.

In order to evaluate these potential costs and benefits of retail electricity pricing reform, this paper provides empirical evidence on the consumption and non-payment responses of electricity customers to retail prices in Delhi, India. Beginning in the late 1990s, Delhi pursued an ambitious set of reforms to its electricity sector that included partially privatizing its distribution segment, formalizing the connections of hundreds of thousands of informal settlement customers, incentivizing investments in improved reliability and service quality, and approximately tripling average retail electricity prices over a decade. Local elections in 2015 brought a populist government into power in part on promises of reversing these price increases. During the period we study, 2015 to 2019, the government reduced average prices for residential customers by 10 to 18 percent, with small residential customers receiving the largest reductions.

Our empirical strategies take advantage of features of Delhi's highly complex retail electricity price schedule to estimate short-run and long-run responses to price changes. Using confidential data including records of about 79 million individual electricity bills, we reconstruct the monthly payment histories of more than 1.5 million domestic, informal settlement, commercial, and small industrial electricity customers served by one of Delhi's three utilities. Pricing reforms beginning in 2014 introduced large notches in the marginal price schedule, and we use a regression discontinuity estimator to analyze the short-run response of customers to non-marginal increases

in the average cost of electricity resulting from these subsidy notches. We find that the leading one to three months' consumption of consumers who are exposed to dramatic non-marginal price increases as a result of consuming above a subsidy notch is very insensitive to these large price increases. For residential customers, the implied elasticities of these estimates range between $-.013$ and $-.0349$. However, during these periods arrears among affected customers rise substantially, though transiently.

We then turn to the long run, employing an instrumental variables (IV) strategy to estimate price elasticities and non-payment responses to price variation. Our IV strategy exploits a rounding rule in the electricity price schedule that generates minute but sustained, plausibly-exogenous variation average electricity prices. We estimate annual price elasticities separately in deciles of annual consumption for domestic and informal settlement customers, and in quintiles for commercial and industrial customers. We find large elasticities across the customer base, ranging from about $-.6$ in the top decile of informal settlement customers to -1.99 in the top quintile of industrial customers. We also find significant annual responses of non-payment to average prices, with effects concentrated among the lower four deciles of domestic and informal settlement customers. For instance, for the bottom decile of informal settlement customers, average arrears more than double in response to a doubling in the average electricity price.

Price elasticities are among the central parameters for efficient retail price design and optimal investment in capacity infrastructure. In addition, they are needed to predict the long-run response to market-based climate policies, whose effectiveness depend on pass-through into retail electricity rates. Retail price elasticity estimates are available in rich country settings ([Borenstein, 2010](#); [Wolak, 2011](#); [Ito, 2014](#); [Jessee and Rapson, 2014](#); [Deryugina et al., 2020](#)). However, well-identified estimates for developing country settings are much sparser. The literature has also generally focused on estimating short-run demand elasticities given the difficulty of finding long-run exogenous variation in energy prices. Long-run elasticity estimates that do exist use state-level data and dynamic panel models rather than quasi-experimental variation ([Kamerschen and Porter, 2004](#); [Dergiades and Tsoulfidis, 2008](#); [Alberini and Filippini, 2011](#)). [Deryugina et al. \(2020\)](#) estimate two-year responses to electricity prices in Illinois and find that households gradually respond to changes in electricity prices. In this paper, we use notches generated in the retail electricity tariff structure by the introduction of subsidies three times during our sample period to

examine the short-run consumption response. We are also able to estimate long-run elasticities using minute time series and cross-sectional variation in the effective electricity price schedule generated by differences in billing cycles and a quirk in the standardization factor used to ensure that consumers face approximately the same price schedule for each unit of consumption. Furthermore, we use these strategies to estimate a negative payment elasticity to the price, which suggests that subsidizing power may generate surplus by raising payment rates. We then illustrate through an analytical framework how the regulator's pricing decision depends on the functional form of non-payment and the relative magnitudes of the demand and payment elasticities.

The subsidies introduced by the Delhi government not only dramatically reduced electricity prices for most residential customers, they also increased the complexity of the price schedule. Standard welfare analysis assumes that consumers can distinguish between fixed and variable costs. However, empirical evidence suggests that consumers may misconceive a change in average price as a change in marginal price ([Liebman and Zeckhauser, 2004](#)). In the case of electricity markets, [Ito \(2014\)](#) finds that consumers respond to average price rather than marginal price, when the marginal price is a step function of monthly consumption, similar to multi-tiered income tax schedules. Monthly electricity consumption is also often difficult to observe, making it challenging to optimize against complex non-linear price schedules ([Borenstein, 2009](#); [Jessoe and Rapson, 2014](#)). While notches in tax schedules have been shown to magnify the behavioral responses to the underlying taxable income elasticity ([Kleven and Waseem, 2013](#)), the lack of salience and optimization failures could mitigate the response to the subsidy. In this paper, we also consider how non-payment affects consumers' response to complex non-linear price schedules.

The rest of this paper proceeds as follows. Section 2 describes the institutional setting and electricity pricing in Delhi. Section 3 presents our data, describes the approach used to infer customer payments from the billing data, and analyzes descriptive statistics. Section 4 describes the empirical strategy and presents results for short-run responses to the subsidy notches. Section 5 describes the empirical strategy and presents results for the long-run responses. Section 6 presents a model of the regulator's pricing decision in the presence of non-payment. Finally, Section 7 concludes with a discussion of the potential policy implications of our findings.

2 Institutional Setting and Policy

2.1 Delhi's Electricity Distribution Segment

While much of India's electricity distribution segment consists of state-owned distribution-only or integrated generation, transmission, and distribution utilities, several of India's large cities, including Delhi, have employed public-private partnership models in distribution ([Pargal and Banerjee, 2014](#)). Under these regimes, private companies acquire distribution grid assets and the right to exclusive retail service territories under pricing and service quality regulations by an electricity regulatory commission. Generally, these franchising schemes guarantee the franchisee a rate of return conditional on a set of performance criteria related to improving service quality.

Delhi pursued the partial privatization of its electricity distribution system under this model alongside the "unbundling" of the Delhi Vidyut Board (DVB), the territory's vertically-integrated, state-owned electricity company, in 2002. Beginning in the late 1990s, the unbundling policy established regulated generation and transmission utilities, an independent system operator called the State Load Dispatch Centre, and a regulatory commission, the Delhi Electricity Regulatory Commission (DERC). The distribution segment was divided into five entities, two small public distribution utilities serving central government and military areas in central New Delhi and three public-private distribution franchises. Private operators for the distribution franchises were selected through a competitive bidding mechanism in which candidate operators bid on five-year aggregate technical and commercial (AT&C) loss reduction targets achievable for a guaranteed rate of return on equity of 16 percent. AT&C losses refer to revenue that is not recovered on energy served due to line losses (technical) and theft and non-payment (commercial). Delhi's three distribution franchises were awarded to two of India's largest infrastructure and industrial conglomerates, Reliance and Tata. Reliance Energy Limited was awarded two of the franchises, one serving south and west Delhi and one serving central and east Delhi. The third, serving north and northwest Delhi was awarded to Tata Power. The franchisees own 51 percent of each utility, with the government of the National Capital Territory of Delhi owning the remaining 49 percent.

At the time of the privatization in 2002, the AT&C losses of the DVB were higher than 55 percent ([Power Finance Corporation Ltd., 2006](#)). This is to say that the DVB collected revenue on only about 45 percent of the energy it served to its distribution grid. While Delhi has few

agricultural markets, which are the source of high AT&C losses in many states, it saw exceptionally high rates of theft and bill non-payment. Until the reforms, regulations had prevented the DVB from serving informal settlements that were home to several million people. As a result, these settlements were served exclusively by illegal connections. Over the past 18 years, Delhi's three private distribution franchises have dramatically increased electricity reliability and reduced losses by investing heavily in grid infrastructure and formalizing connections in informal settlements. By 2005, Delhi's distribution utilities were investing more than twice as much in the grid for every kWh of electricity sold as the country's average ([Power Finance Corporation Ltd., 2006](#)). By the mid 2010s, the AT&C losses of Delhi's distribution utilities had fallen to among the lowest in the country, ranging between 9 and 15 percent ([Power Finance Corporation Ltd., 2016](#)).

2.2 Electricity Pricing in Delhi

A period of retail price increases followed Delhi's distribution reforms in the early 2000s. Referred to as "tariff rationalization" by DERC, the price increases sought to bring retail prices closer to being cost-reflective while supporting the utilities' investment drive. Between 2002 and 2013, average retail prices for residential consumers more than tripled.

February 2015's Delhi Legislative Assembly elections swept a new populist party, the Aam Aadmi Party (AAP), into government in part on the promise of making water free and cutting electricity prices for residential customers by 50 percent. Within weeks of its election, the AAP-led government announced a 50 percent subsidy on the retail electricity tariff for residential customers consuming up to 400 kWh per month, covering about 86 percent of residential bills ([Economic Times, 2015](#)). The subsidies were financed by the government, which reimbursed the utilities for the lost revenue relative to the regulated tariff. On March 1, 2018, the Delhi Electricity Regulatory Commission (DERC) issued a new tariff order with higher fixed charges but lower per-unit rates, which when combined with the AAP government's 50% subsidy for consumption up to 400kWh, increased the average price disproportionately at lower levels of consumption. On May 9, 2018, the Delhi government revised the existing subsidy to a flat rate of INR 2 per unit for customers consuming up to 400kWh per month and approved an additional subsidy of INR 100 on fixed charges for domestic customers consuming up to 100 kWh per month.

As a penalty for failing to pay a bill on time, customers are fined a Late Payment Surcharge at the rate of 18% per year on unpaid dues, which is computed based on the number of days between the payment due date and the date the payment was made. Furthermore, according to the DERC Supply Code 2017, customers are issued a temporary disconnection notice if they do not make pay a bill within three days following the payment due date. The temporary disconnection notice states that the customer will be temporarily disconnected after 15 days if the bill remains unpaid. If the customer is temporarily disconnected, they will no longer receive any power supply, but they will continue to be liable to pay fixed charges to the utility. The service line will remain connected for up to six months, after which the customer will be permanently disconnected if their dues have not been cleared. Once a customer is permanently disconnected, their service line is removed and they can apply for a new connection once all outstanding dues have been cleared. In the summer of 2018, the utility we worked with began replacing traditional meters with smart meters. So far, nearly 200,000 smart meters have been installed. Smart meters enable the utility to remotely disconnect customers and thereby improve enforcement of bill payments.

Fixed charges are levied in proportion to the customer's sanctioned load, which is the load, in kW or kVA, that the utility has agreed to supply the customer. The utility revises the sanctioned load each year by taking the highest average of the customer's maximum demand readings for any four consecutive months in the previous financial year (i.e. April 1 - March 31) and rounding to the lower integer.

3 Data and Descriptive Statistics

The analysis draws on data from two principal sources. First, we obtained billing and power outage records for several years for the universe of customers served by one of Delhi's three private distribution utility companies through a confidentiality agreement. Second, we augmented these data by conducting a household survey of residential customers served by the utility and matching the survey responses to customers' billing history using their unique customer number. The resulting dataset enables us to observe about four and a half years of billing records in addition to detailed demographics and appliance information for the sample of households surveyed. This section describes each of these two data sources in turn and provides summary statistics for the

sample of customers used in the estimation.

3.1 Data

3.1.1 Electricity Bills and Payments

The utility we study serves more than 1 million customers and issued approximately 79 million bills to the residential, industrial, commercial, and public services customers it serves in an exclusive service territory covering a large swath of central Delhi and its outskirts between mid 2014 and the end of 2018. Customers receive electricity bills from the distribution company on approximately monthly cycles for the prior period of consumption.² Typically, bills post two to three days following the close of the billing period, and customers have approximately 14 days to pay their bill. In addition to the total amount payable in Rupees (INR), the customer billing data include total consumption in kilowatt hours (kWh), detailed breakdowns of individual fixed and volumetric charges, subsidies and rebates received, and the due date of the bill.

Because we do not observe payments directly, we impute payment rates and arrears using the sequence of bills received by each customer. Each billing record contains both charges added during the current billing cycle and the total amount payable on the account at the time of posting. The difference between these reflects outstanding balances on the account, which may be either positive or negative. The positive balances reflect either unpaid past-due charges or outstanding charges that have not yet come due. We infer the portion of these positive balances that are past due based on the due dates of each customer's prior bills. This procedure requires several assumptions. First, we are unable to allocate account balances to arrears and outstanding charges that have not yet come due for each customer's first observed bill because we cannot observe the due dates of prior bills. To resolve this problem, we assume that all balances are outstanding charges that have not yet come due. Second, in approximately 95 percent of cases we observe a customer's next bill post following the due date of their prior bill. For these cases, we can observe whether the customer paid the prior bill by the posting date of the next bill, generally about two weeks later, but not whether the customer paid the bill by the exact due date. Therefore, our

²A small proportion of customers served by the utility have pre-paid meters during the later years of the study period. They are excluded from the analysis here.