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Essays on Electricity Economics

By

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To my parents,

Allan & Helen,

for their unwavering and unconditional support.

Contents

Abstract

My dissertation leverages electricity data for an economic investigation of three disparate topics: the effects of the COVID-19 pandemic; the implications of government ownership on the exercise of market power in the Australian National Electricity Market (NEM); and, the unintended consequences of US Clean Air Act regulation on coal boilers.

First, we use high-frequency data on electricity consumption to demonstrate the effect of COVID restrictions on business activity and the mitigating effects of federal support programs—including, Economic Injury Disaster Loans and the Paycheck Protection Program. We find that COVID-mandated business closures led to a 48 to 71 kwh reduction in daily consumption, corresponding to 13% to 20% drop compared to pre-pandemic use. While all firms reduced electricity consumption on average, these reductions are significantly less pronounced for firms that received a federal loan or grant.

Next, we study the intertwined effects of government ownership and market power in the context of the Australian NEM. In particular, we focus on the 2017 direction to place downward pressure on wholesale prices given by the Queensland Government to one of its government-owned generators, Stanwell Corp. We base our analysis on a benchmark model, which estimates counterfactual prices under the assumption of perfect competition. The comparison of actual market outcomes with simulations suggests that the exercise of market power by Queensland generators during high-demand periods decreased after the issuing of the direction. However, we find no evidence of government intervention affecting markups at lower levels of demand.

Finally, we study vintage differentiation in the context of New Source Review—a set of regulations passed within the US Clean Air Act imposing costly sulfur dioxide abatement requirements on new units but not existing ones. We analyze how this differential treatment affected the utilization and retirement of coal boilers. We find that the regulatory differentiation within NSR had a strong effect on both of the internal and external operational margins. Exempted coal boilers were

associated with a 1.5 percentage point increase in probability of surviving an additional year and an increase of around 700 hours to their annual operations.

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Chapter 1 developed from my work as a research assistant on residential and commercial energy efficiency programs at Burbank Water and Power. I am grateful to Katrina Jessoe and Gabriel Lade for asking me to join the research team, for their project management and for their collaboration on data collection and the analysis itself. I acknowledge the generous support of the Sloan Foundation for this research.

Chapter 2 was inspired by my prior experience working in Australia's energy regulation sector. I am grateful to James Bushnell for his support in developing the model and its application to the event of interest. I would also like to acknowledge Gordon Leslie and Frank Wolak who we engaged with at various times during our study and who provided helpful feedback.

Chapter 3 grew from a serendipitous meeting at the Colorado Technology Primer for Economists and Social Scientists held at the Colorado School of Mines in 2018. Despite a preceding week which seemed intent on derailing my participation—including a car crash near the Canadian border, a wildfire in California, and a sleepless drive down the West Coast—I did manage to attend. Interactions with Sylwia Bialek led to a fruitful collaboration, and, more importantly, a life partner. I would like to thank Ian Lange and Peter Maniloff for organizing the Primer. I am grateful to Richard Revesz for his support in developing and progressing the idea. We received excellent research assistance from Bridget Pals and student support from Aaron Baron.

Finally, research is never performed in a (metaphorical) vacuum. Beyond my immediate supervisors and co-authors, there are numerous individuals who made contributions great and small to my work in Davis. From inside out, the Davis Energy Economics Program provided a rich, if challenging, environment to sound out ideas and receive feedback on our research. In particular, I would like to acknowledge the core members of the "Energy Drinks" group—Nicholas Bowden, Benjamin Dawson and Kevin Nakolan—who provided, in equal measure, an excellent academic sounding-board and a legitimate excuse to leave the department early. My cohort provided an inexhaustible source of inspiration and catharsis, including Amanda Lindsay, Anne Riddle, Lila Cardell, Laura Meinzen-Dick and Natalie Popovich. I would like to single out Natalie, in particular, who taught me the meaning of being a Californian, even if I was stubbornly unable to adapt.

Outside of the economics community, there are a number of individuals whose contributions defined my experience in California. Taylor Helgestad and Chris Cogan were instrumental in preventing my seemingly inevitable transition to hermitage. Brett Rudder left me in the dust and dragged my sorry behind up and down too many Northern California trails to count. And Ryan Maher and his *joie de vivre* inexplicably joined me on cross-country journeys destined to go awry. I deeply cherish their camaraderie.

On this path, I had the great fortune to meet my partner, Sylwia, who provided both insightful technical advice and tremendous emotional support, especially during the pandemic. This document, in no small measure, represents her patience, wisdom and encouragement. Finally, I thank my parents, Allan and Helen, for their love and support. It may be trite, but this work could not have happened without you both. All remaining errors and omissions are my own.

Introduction

Electricity markets are fertile ground for economic study. They feature prominently in the industrial organization and resource economics literatures. In part, this reflects the industry's specific advantages, including: product homogeneity, which eliminates the challenges of product differentiation; perfectly inelastic and observed demand, obviating the need for its estimation; known production functions and the availability of cost data; and, a known market mechanism common to all participants. Combined, these features allow economists to peer far deeper into the market's underlying processes and drivers than is typically in most contexts. Moreover, electricity is fundamental within modern, developed economies. Electricity market outcomes are not only a convenient subject of inquiry for economists, but also have considerable welfare implications and, thus, high relevance for policymakers.

My dissertation leverages electricity data as the basis for an investigation of three disparate topics. The first chapter uses electricity consumption data to measure the economic impacts experienced by businesses in Southern California during the early stages of the COVID-19 pandemic. The second chapter studies the relationship between government ownership and market power within the Australian National Electricity Market (NEM). Finally, the third chapter investigates the unintended consequences of US Clean Air Act regulations on coal boilers. Despite the papers' focus on electricity markets, each chapter has economic and policy implications beyond their specific context. These are highlighted in the text. The remainder of this section introduces the work in greater detail.

The first chapter leverages high-frequency data on electricity consumption to demonstrate the effect of COVID restrictions on business activity and the mitigating effects of federal support programs. Using hourly data from the population of commercial customers in a utility and a panel event study framework, we evaluate how COVID restrictions alter total electricity consumption, the time profile of when electricity is consumed, and the probability that an account shuts down.

We interpret these outcomes to be indicative of the business activity levels of individual firms. We find that COVID-mandated business closures led to a 48 to 71 kwh reduction in daily consumption, corresponding to 13% to 20% drop compared to pre-pandemic use. COVID also led to firm exit, with the probability of account closures increasing over the duration of the pandemic. While all firms reduced electricity consumption on average, these reductions are significantly less pronounced for firms that received a federal loan or grant through Economic Injury Disaster Loans and the Paycheck Protection Program. This suggests that federal support programs meaningfully dampened the detrimental effects of COVID restrictions on small businesses.

In the second chapter, we study the intertwined effects of government ownership and market power in the context of the Australian NEM. In particular, we focus on the "Stanwell Direction" made by the Queensland Government in June 2017. The Direction was a formal instruction by the state government to Stanwell Corporation, a government-owned generator, to alter its bidding strategies in order to put downward pressure on wholesale electricity prices. Our analysis first reviews the history of government ownership within the Queensland electricity sector. We focus on the Government's original reasoning for maintaining public ownership, how government decisions affected market structure and concentration, and how high levels of concentration could have precipitated specific market power strategies employed by government-owned generators. We then turn to an investigation of the effects of the Direction on the exercise of market power. We base our analysis on a benchmark model of the NEM, which estimates counterfactual prices under the assumption of perfect competition. The comparison of actual market outcomes with our simulations suggests that the exercise of market power by Queensland generators during high-demand periods decreased after the issuing of the Direction. However, we find no evidence of government intervention affecting markups at lower levels of demand. With respect to customer impacts, we find that the Direction's effects were symmetric for both Queensland and New South Wales customers.

Finally, in the third chapter, we study vintage differentiation in the context of New Source Review—a set of regulations passed within the US Clean Air Act imposing costly sulfur dioxide abatement requirements on new units but not existing ones. We analyze how this differential treatment affected the utilization, retirement and emissions of coal boilers. For the analysis, we develop a new approach to identify whether a boiler was subject to New Source Review. We also collect a novel dataset covering state-level sulfur dioxide regulations. We find that the regulatory differentiation within NSR had a strong effect on the operations of the exempted coal boilers, raising their probability of surviving an additional year by 1.5 percentage points and increasing their operations by around 700 hours annually. It also allowed the exempted units to keep very high emission levels.

CHAPTER 1

COVID restrictions, federal assistance and small businesses: What can we learn from electricity data?

Co-Authors:

Katrina Jessoe and Gabriel E. Lade

1.1. Introduction

Since the beginning of 2020, the COVID-19 pandemic precipitated simultaneous public health and economic crises. To address the former, governments temporarily suspended large sections of their economies. As California was one of the first states in the US to experience community transmission, Governor Newsom issued a state of emergency in early March 2020. This was rapidly followed by a state-wide shelter-in-place (SIP) order and non-essential business closures. While these measures saved lives across the state, they also contributed to the staggering economic dislocation and hardship instigated by the pandemic.[1,2]

The adverse economic effects of the pandemic and public health orders were particularly felt by businesses. A number of early surveys document widespread closures, mass layoffs, and deleterious effects on businesses across the US (Alekseev et al., 2020; Buffington et al., 2020; Fairlie, 2020). Moreover, many business owners anticipated that a longer crisis would lower their ability to reopen afterwards (Bartik et al., 2020*b*). To mitigate these adverse economic effects, Congress passed a series of appropriations bills in early 2020. The most well-known— the Coronavirus Aid, Relief, and Economic Security Act, or CARES Act—included enormous financial relief for small businesses. Specifically, it created the Paycheck Protection Program (PPP) and funded Economic Injury Disaster Loans (EIDL) for pandemic-related damages. Both programs were administered by the Small Business Administration (SBA). Many businesses applied for federal assistance (Buffington et al., 2020), and those that received aid reported fewer layoffs, higher employment, and improved expectations about the future (Humphries, Neilson and Ulyssea, 2020).

Our study aims to further assess how the pandemic has impacted businesses, as well as how public policy may have mitigated the pandemic's harmful economic consequences. Using high-resolution electricity data from Burbank, California, we attempt to answer the following. First, how public health orders impacted business activity and business exits, as measured through commercial electricity use and account closures. These two effects correspond to the intensive and extensive

[1] An analysis by Friedson et al. (2021) suggests that the early SIP in California saved up to 1,600 lives one month after the order. For context, Los Angeles County suffered nearly 300,000 cases and over 7,000 deaths by the middle of Oct 2020 (see CA Open Data). Analyses by Fowler et al. (2020) and Lyu and Wehby (2020) find similar conclusions across the US.

[2] Many studies investigate the economic impacts of the pandemic, see for example Friedson et al. (2021) and Wright et al. (2020).

margins, respectively. Considering both in unison is essential to forming a full picture of the economic harm to businesses resulting from the pandemic. And second, has federal assistance through the PPP and EIDL loan programs helped mitigate the economic fallout. Essentially, we evaluate the effect of COVID-induced openings and closings on business activity and the mitigating effects of federal assistance for small businesses. As we detail below, we started and made substantial progress towards these aims. Further analyses remain to be competed, and as such, we highlight where our work can be extended in the text.

Our primary data source is proprietary advanced metering infrastructure (AMI) electricity data from Burbank Water and Power (BWP). The dataset contains the population of commercial customers from January 2018 to October 2020, including both electricity and billing data. The data are high-resolution in that electricity is measured hourly at the meter level. Such data can be leveraged to recover heterogeneous effects across both hours and businesses. They also offer greater flexibility in modeling the relationships between variables of interest and outcomes (Ghanem and Smith, 2021). For example, through different fixed effects specifications, we can account for potential omitted variables.

We also utilize PPP and EIDL administrative data from the Small Business Administration (SBA). The dataset contains the population of COVID-related federal loans and grants, including their recipient, date of approval, and amount. Given that these data are provided at the business level, we pair it with our high-resolution electricity data over names and addresses. While our analysis is not yet complete, this synthesis is crucial to identify the effect of loans on business activity across days and the heterogeneous effects across hours. The length of our dataset also allows us to assess whether the effect of a loan persisted in the medium-term.

Our setting reflects a situation in which all units receive "treatment" simultaneously, where treatment is synonymous with the ratcheting in and out of COVID restrictions. Thus, throughout our paper, we adopt a flexible panel event study framework where we regress restriction period dummies on a variety of outcome variables, including: business activity, exit and survival.[3] This

[3] Recent developments in quasi-experimental methods have brought increasing attention to panel event study models. These methods are extensions of classic difference-in-differences and two-way fixed effect models. They typically examine the impact of natural experiments, where events are non-randomly assigned to certain units. The following studies form part of a burgeoning literature on panel event studies including Abraham and Sun (2020), Athley and Imbens (2018), Borusyak and Jaravel (2017), Clarke and Schythe (2020), Freyaldenhoven, Hansen and Shapiro (2019), and Schmidheiny and Siegloch (2019).

implicitly assumes that the effects of different closure and opening periods are heterogeneous. We control for possible confounders including weather and COVID case numbers. Our identifying assumption requires that there are no systematic changes over time except for treatment, conditional on covariates. This assumption holds for our analysis of COVID restrictions on business activity and exits. And the corresponding results can be interpreted as causal. However, our analysis of the effects of federal loan receipt suffers from selection bias and should only be interpreted as correlations.

Our "treatment" events correspond to changes in non-essential business closure orders within Los Angeles (LA) County. The County Department of Public Health (DPH) released frequent updates on the scope and intensity of permitted business activity during the COVID-19 pandemic. We rely on their orders to define periods of increasing and decreasing business restrictions, where our dataset distinguishes four major periods:

- The initial closure order commenced on 16 March 2020, which coincided with the State SIP order enacted three days later on 19 March 2020.
- The initial reopening began on 8 May 2020, where the County allowed certain types of non-essential businesses to reopen with modifications. This corresponded with California moving to Stage 2 of the Resilience Roadmap.
- The second closure period commenced on 28 June 2020 and was precipitated by a surge in cases over the summer. Instead of state-wide restrictions, the second closure period was targeted at the county level.
- The second reopening began on 31 August 2020 in conjunction with the development of California's Blueprint for a Safer Economy. All local health jurisdictions in the state were permitted to reopen specified sectors according to their respective COVID metrics.

Our empirical strategy compares business electricity use and account status during these four events with similar periods in previous years, conditional on covariates. Our results are robust to a series of increasingly stringent business and time fixed effects.

Our first major finding is that COVID restrictions had significant and persistent negative effects on business activity. In effect, the restrictions led to large reductions in commercial electricity use. On average, business closure orders in Burbank led to a 64 to 71 kWh reduction in daily business-level electricity use. Partial re-openings experienced in the late spring and early autumn led to a 49 to 62 kWh reduction in daily consumption, relative to the same business over the same time period in pre-pandemic years. Within-day effects were also quite stark with electricity use decreasing significantly across all hours. The largest hourly reductions were observed between the main business hours of 10AM and 5PM. On average these were between 3.5 and 5 kWh, though by the second re-opening period they had reduced to between 2.5 and 3 kWh.

Our second major finding is that COVID restrictions had increasingly adverse effects on business status. The pandemic increased the net-termination of electricity accounts. Moreover, even as restrictions eased, terminations continue to increase. This is despite periods with less onerous restrictions during some months of the sample period. We also perform a complementary survival analysis, which confirms that the probability of exit increases during the pandemic.

We then repeat the analysis and separate out business response based upon the receipt of either a PPP or an EIDL loan. Our hypothesis is that if these loans reduce the detrimental effects of COVID restrictions on business activity, then reductions in electricity use should be less pronounced for businesses who received a loan. This leads to our third major finding that, while all firms reduced electricity use in response to COVID restrictions, reductions are significantly less severe for firms that received federal assistance. That is, federal assistance programs dampen the reductions in business activity for businesses who receive them. For this finding, note that our current empirical methods only permit us to establish correlation and not causation.

The remainder of the paper proceeds as follows. Section 1.2 reviews the literature and summarizes our contribution. Section 1.3 provides background information on the relationship between electricity and economic activity, public health orders within Burbank, and COVID-induced federal assistance programs. Section 1.4 summarizes the data for our analyses. Sections 1.5 and 1.6 present our empirical strategy and results for business activity and exits. Finally, Section 1.7 concludes.

1.2. Literature review

The COVID pandemic and resultant public health directives have precipitated a vast literature. A small sampling include studies investigating its effects on consumers (Alexander and Karger, 2020), labor (Bartik et al., 2020*c*), health (Cicala et al., 2020), and the environment Gillingham et al. (2020). The effects on small businesses have also garnered significant interest in large part due to the harmful impacts of local restrictions juxtaposed by mitigating federal aid. Below we review the literature on these two topics: the effects of COVID and federal assistance on small businesses. We then recap by discussing our contribution to the literature.

1.2.1. COVID and public health impact

Given the lack of data in the early stages of the pandemic, many papers relied on direct responses from small businesses. Some studies present results from bespoke surveys investigating the pandemic. For example, Alekseev et al. (2020) reports results from an online survey garnering over 66,000 responses, while Bartik et al. (2020*b*) conducted a survey of around 6,000 small businesses that were members of the Alignable business network. Other papers rely on surveys administered by federal agencies using nationally representative data. These include Buffington et al. (2020) who use the Small Business Pulse Survey run by the Census Bureau, while Fairlie (2020) study the Current Population Survey published by the Bureau of Labor Statistics. All survey studies find that the impacts from the pandemic on small businesses were deleterious and persistent across all sectors of the economy.

Instead, our paper primarily relates the literature using indirect, high-frequency indicators to provide real-time assessment of the economic effects of the pandemic (see e.g., Bartik et al., 2020*a*; Chen et al., 2020; Chetty et al., 2020). Electricity as a publicly-available, hourly indicator has attracted wide attention in this regard (Agdas and Barooah, 2020; Bahmanyar, Estebsari and Ernst, 2020; Benatia, 2020; Benatia and Gingras, 2021; Buechler et al., 2020; Chen et al., 2020; Cicala, 2020*a*; Fezzi and Fanghella, 2020; Ghiani et al., 2020; IAEE, 2020; Janzen and Radulescu, 2020; Leach, Rivers and Shaffer, 2020; López-Prol and O, 2020; Ruan et al., 2020). These studies all use real-time changes in electricity data to proxy for economic activity in various countries around the globe. However, they all assess aggregate consumption without considering potential heterogeneous effects by sector, e.g. residential and commercial.

We are aware of only three papers addressing the impacts of the pandemic on electricity at the sectoral level. Bover et al. (2020) analyze the impact of the pandemic on electricity use patterns in Spain. They assess changes in both daily and monthly consumption based on a timeseries approach conditioning on weather, seasonality and holidays. Essentially, they remove confounding variation and compare residuals before and after the start of the pandemic. In particular, they leverage information on electricity tariffs and market access in order to infer sector classification. At both the daily and monthly scales, they find that while commercial electricity demand fell substantially, it was replaced in part by a parallel increase in residential demand.

A closely related paper, Cicala (2020*b*) estimates how electricity consumption changed in the US during the initial stages of the pandemic. The paper performs two distinct analyses. First, using hourly data from Texas aggregated by customer class and a timeseries approach, the author explores how daily residential routines changed during the pandemic. Second, using monthly data from the Energy Information Administration (EIA) and a two-way fixed effects model over utilities, the author identifies the impacts of the pandemic on commercial and residential customers, separately. The paper reports a reduction in commercial paralleled by an increase in residential demand.

Finally, Cheshmehzangi (2020) conducts a longitudinal energy-use survey among 352 Chinese households. The survey was undertaken at monthly intervals during the pandemic and investigated diversified energy use, beyond simply electricity. Their results suggest strong positive impacts on cooking, entertainment, heating and cooling, and lighting, which translated into increased overall household electricity demand.

1.2.2. Federal stimulus response

A number of papers assess the effectiveness of federal COVID assistance for small businesses. To our knowledge, these papers focus exclusively on the PPP. Essentially, they endeavor to determine how successful the program was at meeting its stated goal of maintaining employment after the implementation of widespread public health measures. Some studies analyze unemployment directly, while others assess the program through indirect measures of hours worked or business survival. They also vary based on their designs, namely: surveys, instrumental variables (IV), and difference-in-differences (DD).

Some studies use bespoke surveys to query businesses directly. They both find that the PPP had a positive effect. For example, Humphries, Neilson and Ulyssea (2020) show that small businesses that received PPP loans were less likely to have fewer employees than in January 2020, while Bartlett and Morse (2020) find that PPP receipt increases business survival probabilities.

The IV-design papers utilize aggregated cross-sectional PPP data to regress an outcome of interest on a measure of PPP loans. However, the PPP measure is potentially endogenous as firms in high unemployment regions may be more likely to access the program. Identification rests on performing a two-stage least squared regression using an instrument for PPP receipt. Each paper proposes a different instrument based on heterogeneity in loan access. Barraza, Rossi and Yeager (2020) exploit the density of banking offices that were members of the SBA and find statistically significant effects on unemployment. Bartik et al. (2020*a*) use variation in exposure to large banks which were found to process applications slower compared to small banks and credit unions. They find that the program increased business survival by between 14 to 30 percentage points, though it had no effect on employment. Granja et al. (2020) leverage PPP loan processing relative to pre-pandemic small business loan volumes.[4] They find modest effects on hours worked and business revenues and no effects on unemployment insurance claims and business shutdowns. Given the similarity in methods, the inconsistency in results for similar outcome variables above is likely driven by different data sources.

Lastly, two studies use the PPP's size-eligibility threshold of 500 employees to study the employment effects of the program. Through a DD design, they exploit local variation around larger firms in order to compare employment before and after PPP availability and above and below the size threshold. The identifying assumption requires that businesses below the threshold would have experienced comparable employment changes to firms above it, conditional on covariates. Given the threshold represents the cutoff for a large business as defined by the Census Bureau, the validity of the assumption may be questionable. Even by restricting the window around the threshold, smaller businesses may be systematically different due to a lack of liquidity, smaller reserves, less extensive banking relationships, and/or fewer staff to apply for government assistance. Nevertheless, Autor et al. (2020) use a DD event study design which finds that the PPP increased employment

[4] In addition to the regional analyses, Granja et al. (2020) also perform a unit-level regression based on matching PPP loan and proprietary payroll data. They assess PPP loan timing and whether differences affected short-term employment outcomes. They instrument using heterogeneity in regional PPP lending principals.

at eligible firms. Chetty et al. (2020), on the other hand, use a classic DD design and conclude that the PPP had an insignificant effect on employment.

1.2.3. Contribution

Our paper makes a number of novel contributions. First, we extend the understanding of how the pandemic affected commercial electricity demand. While some papers have provided commercial analyses, most focus on residential or aggregate impacts. Moreover, given that our dataset is both high-resolution and represents the population of businesses in Burbank, we are not necessarily constrained to aggregate sectoral analyses. While we have not presented it here, we plan to investigate heterogeneity at the industry level.

Second, we believe we are the first to assess the combined effect of both the PPP and EIDL programs. This is important as all extant papers have focused exclusively on the PPP. However, the EIDL and EIDL Advance are functionally similar to and operate simultaneously with the PPP, such that, their omission could serve to confound loan receipt results.

Third, to our knowledge, we are the first to study the effects of federal loan receipt using electricity data. This confers a number of advantages. Instead of assessing the effect of loan receipt on standard economic measures, such as employment or revenue, we can assess business activity at the hourly level. Thus, it is possible to retrieve heterogeneous effects across the hours of the day. Also, the majority of studies reviewed identify regional effects of loan receipt. In contrast, the high spatial resolution of our data means we can recover matches at the business level.

This latter point deserves further elaboration as it leads to a number of intriguing extensions. Our empirical methods in this version of our paper are similar to Bover et al. (2020) and Cicala (2020*b*). However, our dataset contains additional cross-sectional variation which will eventually allow us to apply more sophisticated econometric techniques. As mentioned, these could include efforts to identify COVID-related effects at the industry and even the unit level. Further, we are limited to a correlations analysis with respect to federal loans. Improved matches may allow us to overcome the inherent loan receipt selection bias. If so, it will serve as an additional data point from which to evaluate the success of federal COVID relief programs for small businesses.

1.3. Background

Our paper exploits the introduction, tightening and loosening of COVID closure orders on business activity and exit as measured using electricity data. Below we detail the underlying relationship between electricity and business activity, the timberline of relevant public health orders, and the federal support programs deployed to lessen the harm of pandemic-induced restrictions.

1.3.1. Electricity and business activity

Underpinning our analysis are the twin assumptions that: (1) electricity use is a proxy for business activity; and, (2) electricity account terminations are a proxy for business exits. The persuasiveness of our results rests on the correlation between electricity and activity. Recent evidence from Bover et al. (2020) suggests that commercial and industrial electricity use remains unambiguously correlated with economic activity. This remains the case despite a weakening of the relationship due to improvements in energy efficiency (Hirsh and Koomey, 2015; Metcalf, 2008), the increased weight of the service sector (Buera and Kabosk, 2012), and changing patterns of electricity consumption due to the pandemic (Dingel and Neiman, 2020).

Electricity has long been noted to have a strong correlation with economic growth (e.g., Henderson, Storeygard and Weil, 2012; Kraft and Kraft, 1978; Stern, 2018). Despite concerns over the robustness of the relationship, it remains a particularly appealing proxy for business activity. The benefits in our context are reinforced due to its lack of substitutes and high-resolution (Cicala, 2020*b*). For the former, electricity is an essential input for daily life in developed economies. While business functions are incredibly varied and diverse, most now rely on electricity as their primary fuel source, particularly within urban areas. Moreover, as digitization has increased, so too has the reliance on electrical energy to power essential business tools, in particular information and communication technologies. Affordable alternatives either do not exist, are impractical or damage the environment. Consequently, most businesses cannot operate without a reliable and secure source of electricity rendering it highly correlated with business activity.

For the latter, the transition to smart metering infrastructure makes available high-resolution electricity data across both space and time. It is now possible to assess high-frequency changes in economic activity by tracking electricity demand. Thus, effects that may be obscured or lost in the aggregate, can instead be identified at the business-hour level. This is particularly important when studying commercial compared to residential electricity consumption as the former is significantly more idiosyncratic.

1.3.2. Public health orders

Our empirical setting is the City of Burbank which hosts a population of around 100,000 people and is located in LA County, California. BWP is the municipal utility owned and operated by the city. Figure 1.1 contrasts its service territory with that of the LA Department of Water and Power (LADWP), its neighbor and the largest municipal utility in the US.

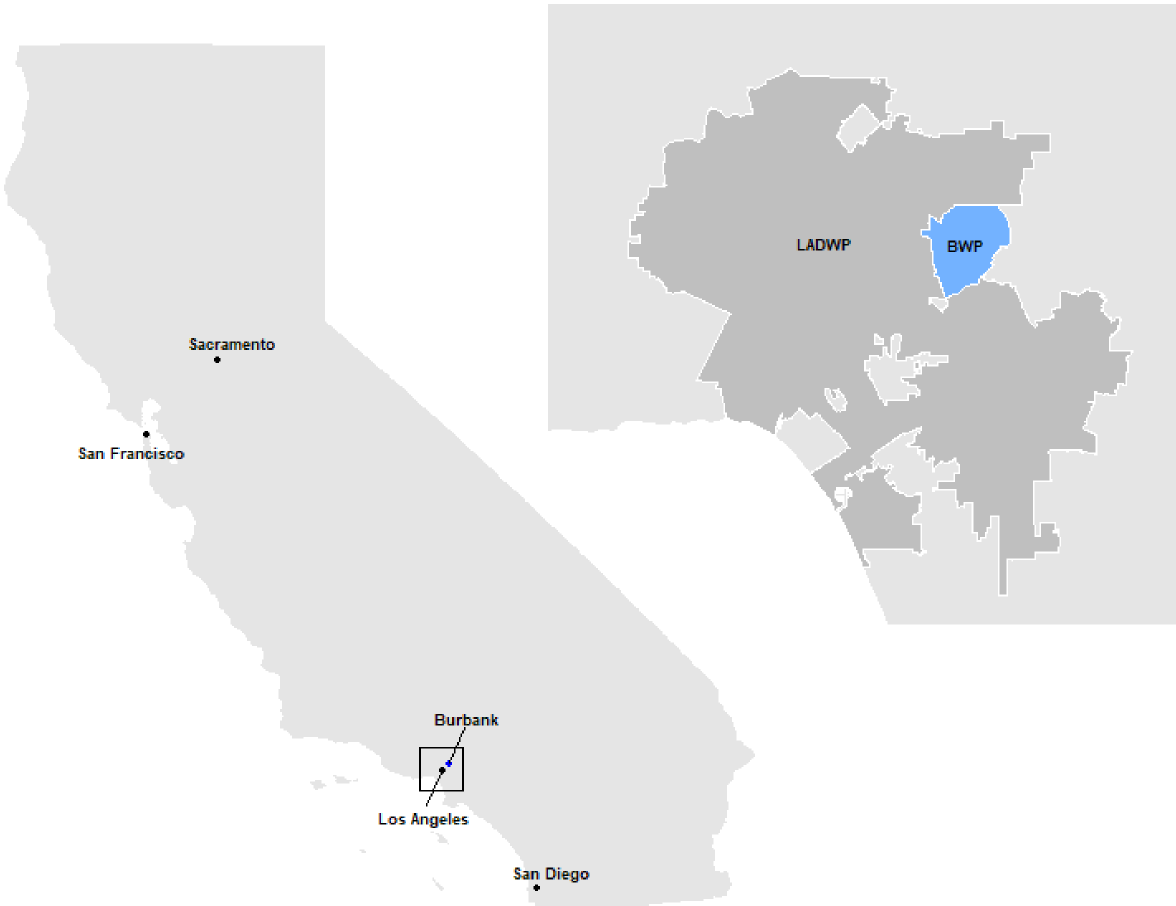
The city falls under the purview of the public health guidelines set by both LA County and the State of California. The county and state responded to the COVID pandemic through the implementation of an evolving list of restrictions. Through the Governor's Office and the State Department of Public Health Department (DPH), California mandated both shelter-in-place (SIP) and non-essential business closures. The former require all residents to remain located in place for all but essential activities, such as grocery shopping, retrieving prescriptions, care giving, exercise, etc. The latter require businesses to cease operations, or alternatively, delineate industries that can remain open.

LA County operationalized the state-level orders for areas under their jurisdiction, including Burbank, through equivalent directives from their DPH. In order to comply with requirements established by the state, LA County updated its public health orders as frequently as necessary – sometimes even on a day-to-day basis. The top half of Figure 1.2 provides an overview of the major public health orders affecting the Burbank through to the end of October 2020.

The first confirmed COVID-19 case in LA County arrived on 22 January 2020.[5] Shortly thereafter, community transmission began to rise precipitating the declaration of a State of Emergency

[5] Ryan, H, St. John, P, and Liang, X. 2020 "The surprising story of the salesman who became L.A.'s first known COVID-19 patient." LA Times, 21 Aug.

Figure 1.1. BWP's service territory within California



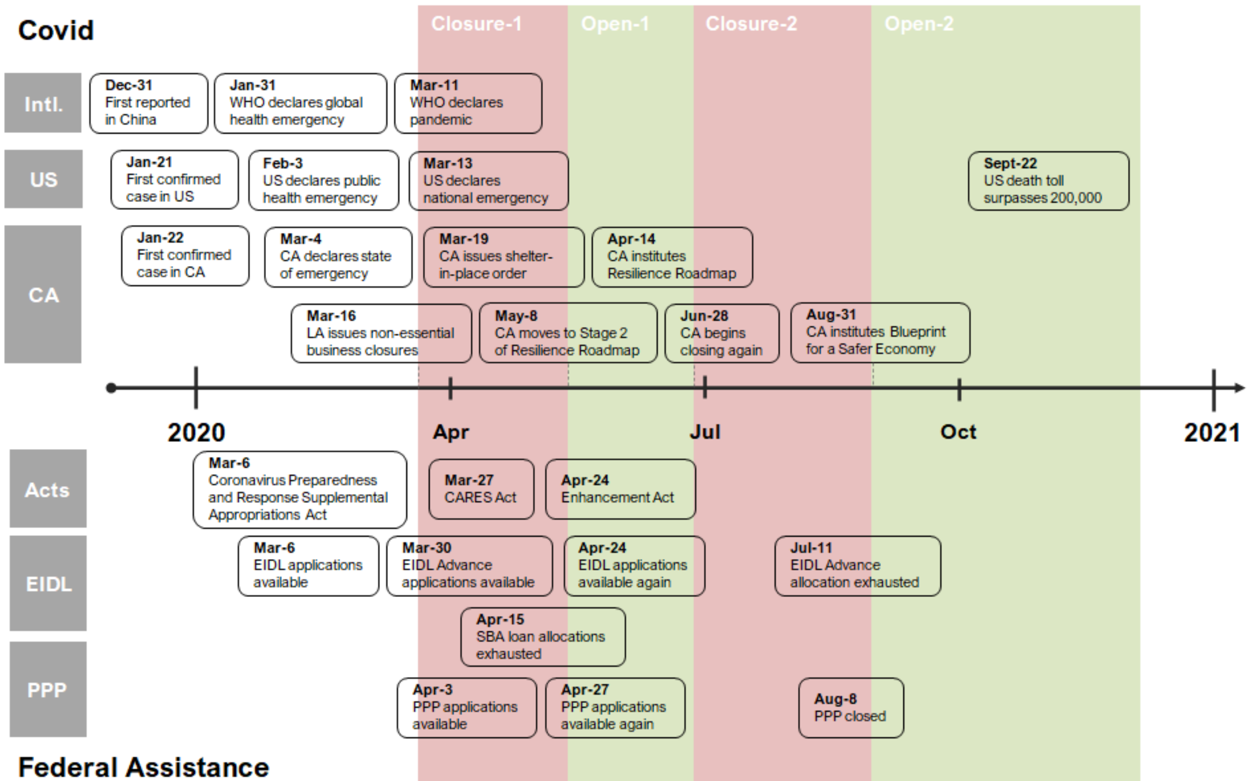
Notes: The map illustrates the geographical location of Burbank Water and Power (BWP). It also contains a portion of the service territory for its neighboring utility, the Los Angeles Department of Water and Power (LADWP).

for California as a whole on 4 March 2020.[6] The declaration was primarily to raise public awareness and to release state funds and resource to help fight the pandemic. It did not mandate social distancing or other behavioral restrictions, such as mask mandates.

As one of the earliest areas experiencing wide community transmission within California, LA County acted in advance of the state by mandating the closure of some non-essential businesses on 16 March 2020. The order prohibited gatherings of 50 or more and required the closure of bars and nightclubs without food service, fitness centers, theaters, bowling alleys and arcades. These closures along with similar ones in the Bay Area catalyzed state action three days later.

[6] https://covid19.ca.gov/safer-economy

FIGURE 1.2. COVID-19 pandemic and assistance timeline



Notes: The figure presents a timeline of events starting in late 2019 through to the end of October 2020. The top half of the timeline summarizes COVID-related events, including important national and international dates as well as restrictions mandated by both the State of California and LA County. The bottom half of the timeline summarizes federal assistance events, including major Acts of Congress and specific dates related to the PPP and EIDL programs. Red and green shaded areas represent closing and opening restriction periods within LA County.

On 19 March 2020, California was the first in the country to mandate a state-wide SIP order. Known as Executive Order N-33-20, its aim was to establish consistency across the state in order to slow the spread of COVID-19. It restricted residents to stay at their place of residence and included a non-essential business closure order. For the closure directive, all businesses except those necessary to maintain operational continuity of the federal critical infrastructure sectors were required to close.[7] While the order has changed form – namely, the "Resilience Roadmap" and "Blueprint for a Safer Economy" – it remained in effect through mid-2021 under the original Executive Order.

[7] There are 16 federal critical infrastructure sectors defined by the Cybersecurity and Infrastructure Security Agency (CISA) under the Department of Homeland Security. See https://www.cisa.gov/identifying-critical-infrastructure-during-covid-19 for further information.

The Resilience Roadmap was announced by Governor Newsom on 14 April 2020. The fist stage of the Roadmap defined six indicators which would inform the modification of the state-wide SIP order. These included community monitoring, prevention, health care capacity, the development of therapeutics, and the ability to socially distance. The Governor did not confirm a precise timeline for modifying the order and instead noted that the indicators would serve as the underlying criteria for making any such decision.

The initial reopening began on 8 May 2020, when California moved to the second stage of the Resilience Roadmap, which reintroduced activities in a phased manner by county and sector. LA County issued a sister order which allowed certain types of non-essential businesses to reopen with modifications, such as curbside pickup, delivery only, and capacity limits. At first, this was limited to retail stores where social distancing was possible: bookstores, florists, clothing and shoe stores, sporting goods stores, toy stores, music stores, and car dealerships. Subsequent orders through May and June permitted the reopening with modifications of additional non-essential businesses, including but not limited to: bars and restaurants, entertainment and gambling venues, gyms, religious services, offices, and personal care services.

The second closure period commenced on 28 June 2020 and was precipitated by a surge in cases during the summer months. Instead of state-wide restrictions, the second closure period was targeted at the county level. To begin, the California DPH released guidance on the closure of bars within counties experiencing high case numbers. This included LA County which promptly issued an updated order to align with the state directive and immediately closed bars, breweries and wineries. Subsequent county orders through July and August either reduced operations or fully re-closed other non-essential businesses.

The second reopening began on 31 August 2020 in conjunction with the development of California's Blueprint for a Safer Economy. The Blueprint for a Safer Economy replaced the Resilience Roadmap with a localized SIP order tailored to COVID conditions within each county. Thus, all local health jurisdictions were permitted to reopen specified sectors according to their respective COVID metrics. Essentially, it imposed risk-based criteria on tightening and loosening allowable activities – that is, instead of open vs. closed, sectors could be partially opened based on county case and positivity rates. LA County subsequently engaged in a phased reopening of non-essential businesses from September through November.

Table 1.A.1 in Appendix 1.A provides further details on the state and county government actions described above.

1.3.3. Federal loan programs

To mitigate the harm to businesses from both the pandemic and the subsequent closure orders, Congress established two major small-business assistance programs: the PPP and EIDL. These programs were created by a series of appropriations bills passed in early 2020 and were administered by the SBA (Bartik et al., 2020*d*; Dilger, Lindsay and Lowry, 2020). The bottom half of Figure 1.2 provides a timeline for the implementation of the two major federal assistance programs.

The scale of these assistance packages were enormous. On 6 March 2020, Congress specified the coronavirus as a disaster under the EIDL program. Thus, economic injury from the coronavirus became an eligible EIDL expense and loans for such purposes were made available immediately through the SBA from existing appropriations.[8] These funds were eventually supplemented by an additional $50 billion for EIDL loans and $20 billion in EIDL Advance grants. On 27 March 2020, Congress created the PPP through the CARES Act. To expedite delivery of the funds, PPP loans were guaranteed by the SBA but administered through private banks. The program was appropriated $659 billion in two rounds which were exhausted by 8 August 2020. Table 1.B.1 in Appendix 1.B provides a detailed legislative history.

Both the PPP and EIDL programs primarily function as loan programs. Eligible businesses are defined as those with primary residence in the US, operating before 16 February 2020, and with 500 or fewer employees.[9] Small businesses were eligible to apply for both; however, the loans could not be used for the same purpose.

The CARES Act stipulated that the PPP must be used for payroll costs and certain eligible non-payroll costs only. As such, its primary purpose was to encourage labor retention and reduce

[8] Prior to its COVID-induced expansion, the EIDL program offered businesses affected by a declared disaster financial support for uninsured losses and operating expenses that could have been met had the disaster not occurred. Declared disasters include civil unrest and natural disasters such as hurricanes, flooding, and wildfires.

[9] Those with greater than 500 employees may still be eligible based on industry-specific size standards.

Table 1.1. Comparison of PPP versus EIDL programs

	PPP	**EIDL**
Description	Low-interest, medium-term loan program where applications are processed through a network of private lenders across the US.	Competitive-interest, long-term loan program where applications are processed by the SBA; includes the EIDL Advance where up to $10,000 may be requested separately or in conjunction with a full EIDL loan.
Purpose	To meet operating expenses, primarily payroll.	To meet various financial obligations and operating expenses.
Max	$10 million	Six months of working capital
Terms	Interest of 1% repaid over 2 to 5 years and deferred for 1 year with no collateral and no personal guarantee required.	Interest of 3.75% repaid over up to 30 years where collateral is required for loans over $25,000 and personal guarantees for loans exceeding $200,000.
Forgivable	Yes, if all employee retention criteria are met and funds used for eligible expenses.	No, loan may be repaid at any time with no prepayment penalties.

employment insurance claims through low-interest, medium-term loans. The federal government offered terms of 1% interest repaid over two to five years with neither collateral, nor personal guarantee required. Crucially, a loan could be converted into a grant, if the borrower met all employee retention criteria and funds were used for eligible expenses. This is equivalent to the loan being forgivable.

EIDL funds, on the other hand, could be used to cover a broader array of capital and operating expenses, such as health care benefits, rent, utilities, and fixed debt payments. Its purpose was to provide short-run cash flow support to keep businesses open and operating. The EIDL for COVID-related damages mirrored the existing program in that it offered competitive-interest, long-term loans with applications processed by the SBA. Terms included an interest rate of 3.75% with repayment of up to 30 years. Collateral was required for loans over $25,000 and personal guarantees for loans exceeding $200,000. Unlike the PPP, the EIDL was not forgivable. In addition to the main EIDL loan, the program also consisted of the EIDL Advance grant which was not repayable.[10]

[10] Originally, businesses that received an EIDL Advance in addition to the PPP necessarily had the amount of the EIDL Advance grant subtracted from the forgiven amount of their PPP loan. However, this stipulation was later eliminated under the American Rescue Plan Act in 2021.

The grant provided $1,000 per employee up to $10,000 total and could be requested separately or in conjunction with an EIDL loan. Additional details on both programs are provided in Table 1.1.

Despite the differences between the programs, they both functioned as rapid cash injections to help small businesses mitigate the effects of a once-in-a-century pandemic. Broadly, we would expect each to increase business activity and reduce the number of exits. This should correspond to increased electricity use and reduced electricity account closures, respectively. The programs, in this respect, can be considered to be equivalent.[11]

1.4. Data

We assemble an business-level primary data set comprised of hourly interval data on electricity use, monthly billing data, industry classification, and participation in federal small business loan programs. These data cover the universe of commercial customers in BWP's service territory and are supplemented with information on COVID-19 case numbers and government public health orders.

1.4.1. Electricity use and billing data

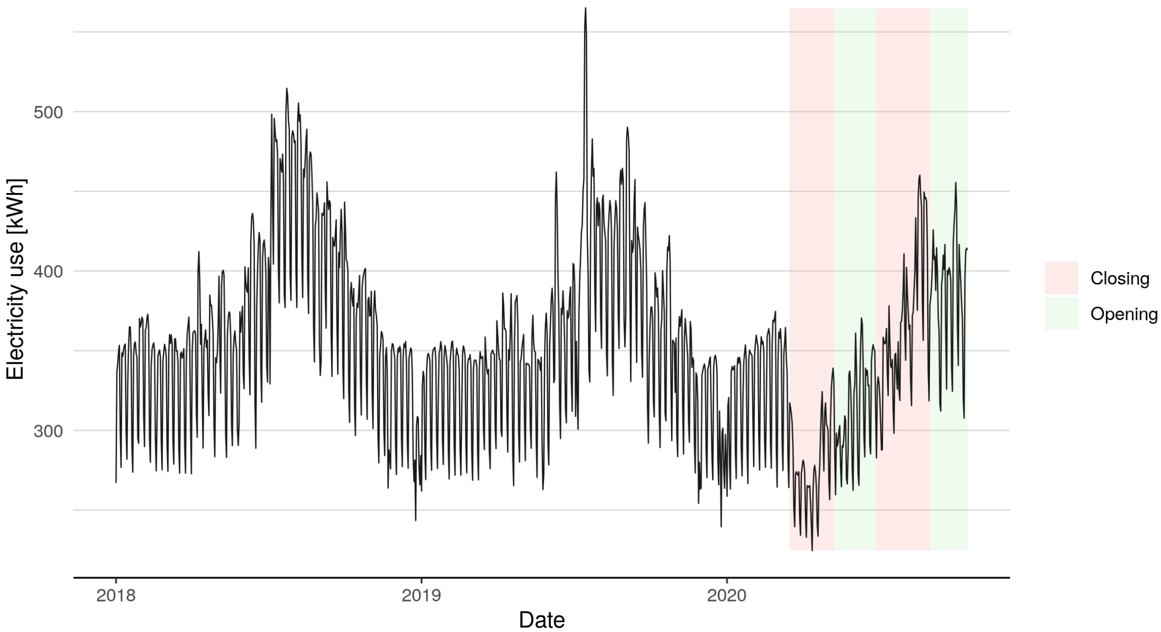
We obtained proprietary electricity use and billing data from BWP.[12] The dataset contains sub-hourly electricity data for the population of commercial customers within their service territory from 1 Jan 2018 up to and including 15 Oct 2020. This was supplemented with the corresponding set of monthly billing data. The high-frequency metering data were aggregated up to the business-hour or business-day level, where a business is defined as a unique name-account-address tuple. Thus, meters at the same address under the same account were aggregated. Using this definition, there were 7,722 businesses in the sample.[13] Figure 1.3 displays average daily usage across all

[11] Nevertheless, this does not preclude heterogeneous outcomes. It is conceivable that size, term and purpose of the received loans could influence the strength and timing of business activity. For example, the response to the long-term commitment of an EIDL loan is likely to be different to a small short-term injection of cash through the EIDL Advance grant. Moreover, any effects may be attenuated for those businesses receiving multiple loans.

[12] The data are obtained under nondisclosure agreement with the utility.

[13] Through our analysis, we found that some businesses were associated with multiple accounts and/or units at the same address. Hence, we test the robustness of our results against an alternative business definition: name-street pairs. Using the alternative definition, the number of businesses in the sample reduces to 5,852. See Appendix 1.D.2 for the alternative analysis.

Figure 1.3. Daily average electricity use per business



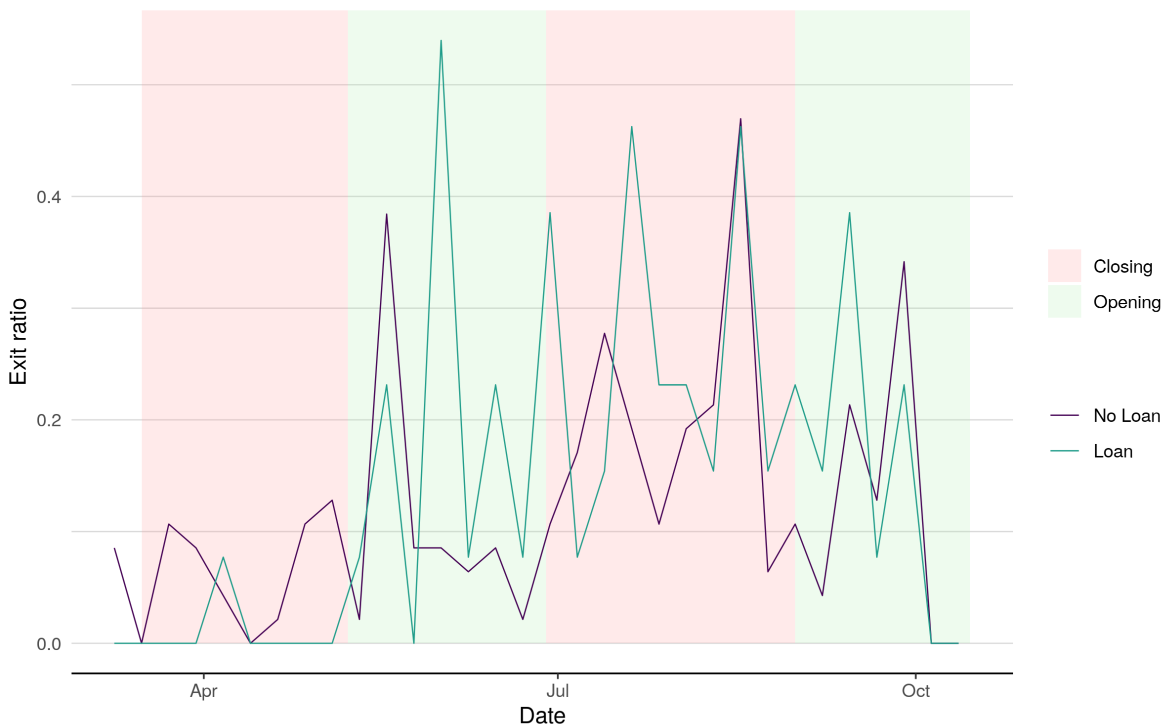
Notes: The plot presents average daily electricity usage per business between 1 January 2018 and 15 October 2020. Businesses are defined as name-account-address tuples and restricted to the 14 industries identified in Section 1.4.2. Shaded areas represent closing and opening periods within LA County.

businesses. The shaded areas signify the tightening and relaxing of LA County public health orders related to the pandemic, where red and green represent closing and opening, respectively.

The first red shaded area corresponds to the LA County shutdown order on 16 Mar 2020 – mandating the closure of bars, gyms, theaters, and entertainment venues – and followed shortly after by the state shelter-in-place order on 19 March 2020. Average daily electricity use drops precipitously after these public health interventions. After the initial closure period ends, usage begins to increase surpassing pre-pandemic levels during the summer months. The raw averages shown in Figure 1.3 illustrate a correlation between COVID restrictions and daily commercial electricity use.[14]

[14] Prior to the beginning of the pandemic, we observe weekly and seasonal patterns that are characteristic of electricity use in Southern California. Weekly variation cycles through weekday highs and weekend lows, while seasonal variation cycles through summer peaks and winter troughs. The latter is correlated with increased air conditioning in Burbank during the summer months in contrast to its relatively mild winters.

Figure 1.4. Exit ratio by loan receipt



Notes: The plot presents exit ratio by week from 9 March to 15 October 2020. The exit ratio is calculated as the net account change over number of accounts on 1 January 2020. Businesses are defined as name-account-address tuples and restricted to the 14 industries identified in Section 1.4.2. Shaded areas represent closing and opening periods within LA County.

Figure 1.4 depicts the exit ratio by week since the first shelter-in-place order was issued. The numerator denotes the number of exits and the denominator measures the number of accounts on 1 January 2020. The purple line plots this ratio for businesses which did not receive a loan while the green line plots it for those which did. From the plot it is clear that, during the first closure period, firms that did not receive federal support had a higher probability of exit. This is confirmed through a two-sample t-test, where the resulting t-statistic is around 2.51 indicating that we reject the null hypothesis of equal means at the 95% confidence level.[15] In other words for the first closure period, the mean exit ratio for those who received loans is significantly higher than those who did

[15] A two-sample t-test compares the means of two groups under the assumption that both samples are independent and normally distributed with unknown but equal variances.

not. In later periods, however, we fail to detect systematic differences in the exit ratio based on the receipt of a loan.[16]

1.4.2. Industry classifications

Industry classifications allow us to explore heterogeneity in the response to restrictions and the receipt of federal support across business type. To determine the industry type for each account in our data, we combined four different data sources to develop a NAICS-account mapping. First, BWP provided an internal matching of NAICS-account pairs. Due to a lack of match accuracy and specificity, we supplemented the original dataset with a number of other sources. Next, we scraped the the California Employment Development Department (EDD) "Find Employers" online search for all businesses within Burbank.[17] This registry provides business names, addresses, employment number categories, and NAICS codes up to the sixth level of specificity. We also obtained NAICS codes from the PPP dataset on federal loans. Lastly, we verified NAICS codes manually by researching businesses and addresses through online search and mapping tools. To synthesize the data sets, we standardized addresses with the Census Bureau Geocoder and then proceeded to match on business names and addresses.[18]

Our analysis restricts its attention to the industries listed in Figure 1.5. These industries were selected since they are either well represented in BWP's service territory and/or likely to be affected by non-essential business closures. Using the classifications identified in Figure 1.5, we reduce our original sample of 7,722 to 4,813 businesses.[19]

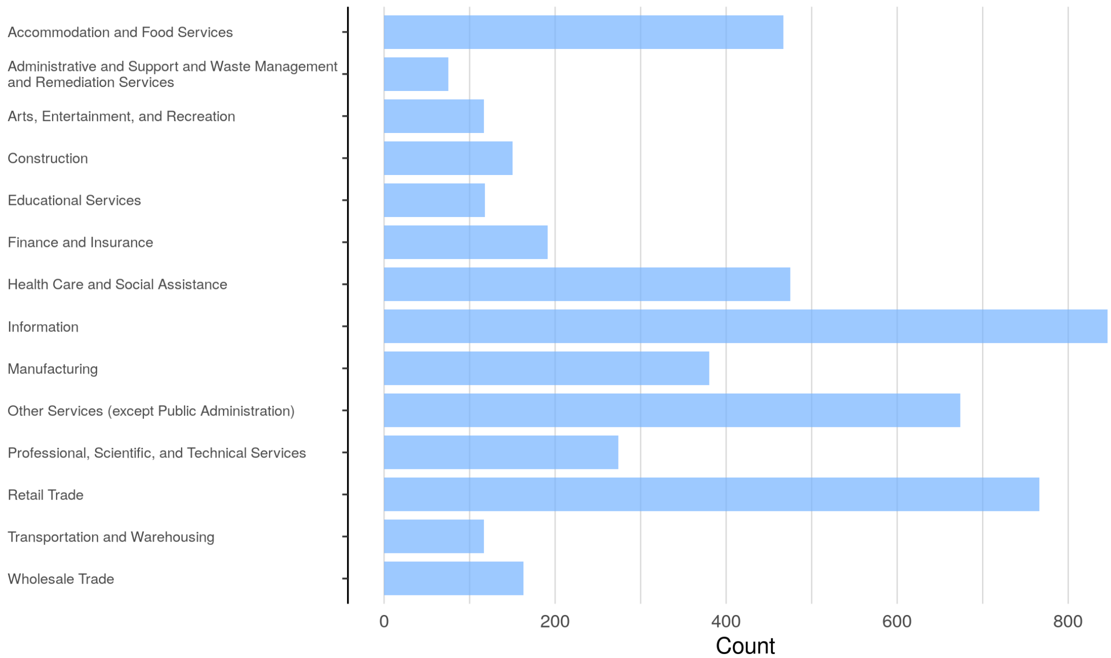
[16] The t-statistics for the mean exit ratio during the first opening, second closing and second opening periods were -0.79, -0.92 and -0.50, respectively. Across the entire post-pandemic period, the mean exit ratio was not significantly different based on receipt of a federal loans. The t-statistic was -0.67 indicating that we fail to reject the null hypothesis at the 95% confidence level.

[17] See www.labormarketinfo.edd.ca.gov/aspdotnet/databrowsing/empMain.aspx.

[18] See https://geocoding.geo.census.gov.

[19] Using the name-street pairs as the definition of a business, there are 5,852 businesses in the sample, which reduces to 4,270 given the selected industries. See Appendix 1.D.2 for the alternative analysis.

Figure 1.5. Count of businesses by NAICS-2 industry classifications



Notes: The plot displays the count of businesses by NAICS-2 industry classifications within our electricity dataset from BWP. Businesses are defined as name-account-address tuples.

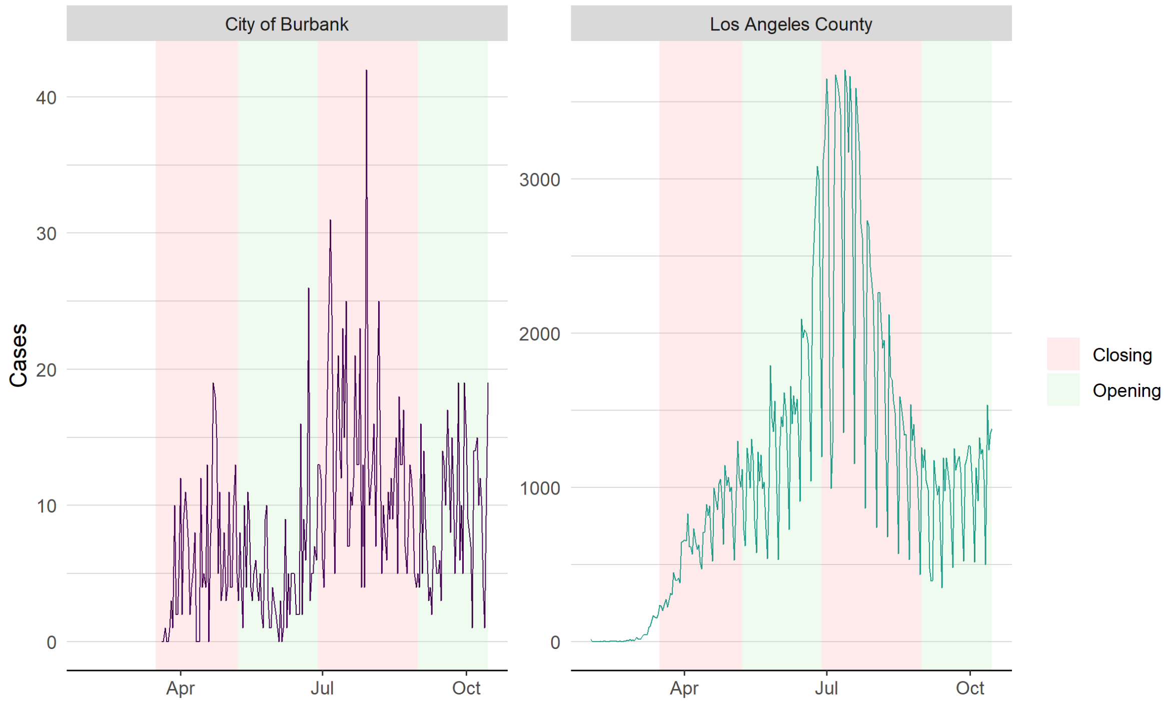
1.4.3. COVID cases and public health orders

COVID-driven changes in business activity may also be a function of demand. As community transmission and case counts increase, demand for business services may decrease irrespective of the stringency and/or presence of COVID restrictions. County-level daily case data are available from the California DPH.[20] Daily COVID cases in the City of Burbank are available through media releases from the LA DPH, and were scraped from its webpage.[21] Figure 1.6 presents case numbers for both Burbank and LA County through the middle of October 2020.

Within California, businesses were subject to state, county, and city orders. We manually compiled restriction scope and effective dates from government sources starting on 1 March 2020

[20] CA Open Data, see data.chhs.ca.gov/dataset/covid-19-time-series-metrics-by-county-and-state.
[21] LA County DPH, see publichealth.lacounty.gov.

FIGURE 1.6. Count of COVID-19 cases in Burbank and Los Angeles County



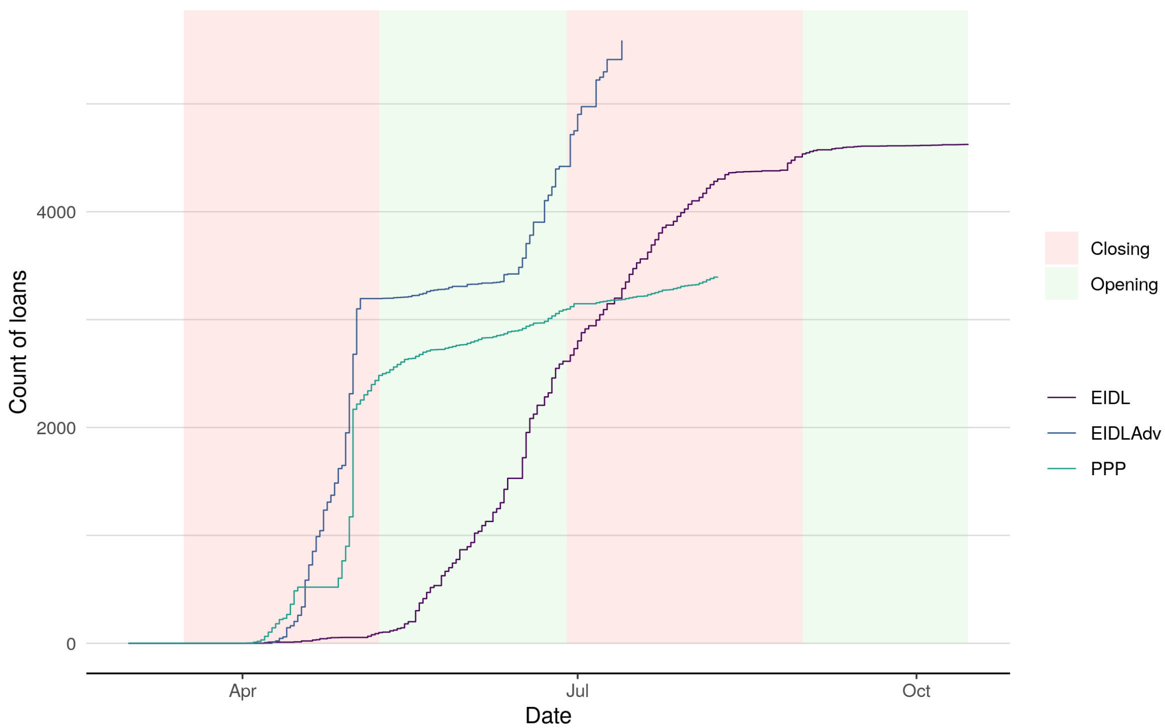
Notes: The plot reports COVID case numbers within Burbank and LA County. Shaded areas represent closing and opening periods within LA County. Sources are described in the text.

and continuing through to mid-Oct 2020.[22] Statewide and regional health orders were obtained from California state government and DPH websites. County-imposed policies were obtained from the LA County DPH website. We also verified if the City of Burbank issued additional restrictions by searching the City of Burbank website and local news outlets.

The dataset identifies both community-at-large SIP orders and non-essential business closures. Dates reflect the day the policy went into effect, instead of issuance or announcement. Moreover, we consider only written and mandatory directives. We define mandatory SIP orders as directives where all residents are to remain in their place of residence unless performing essential activities, such as those related to healthcare, grocery stores, working at essential jobs, or outdoor exercise. We define non-essential business closure orders as those requiring businesses in multiple industries to

[22] The public health orders dataset collected for this paper, while narrower in geographical in scope, mirrors others developed in the wake of the COVID-19 pandemic. Alexander and Karger (2020) and Goolsbee et al. (2020) manually collect state and local government shelter-in-place orders, while Brzezinski et al. (2020) and Gupta et al. (2020) use county level information from the National Association of Counties.

FIGURE 1.7. Count of federal loans awarded to Burbank businesses



Notes: The plot presents counts of federal COVID-related loans awarded to Burbank-registered businesses between 16 March and 15 October 2020. It includes timeseries for the EIDL, EIDL Advance and PPP programs. Shaded areas represent closing and opening periods within LA County. Sources are described in the text.

cease operations. LA County both instructed some sectors to close as well as delineated those that could remain open based on the Essential Critical Infrastructure guidance from the US Department of Homeland Security. As far as practicable, non-essential business closures were disaggregated by industry.

1.4.4. Federal small-business loans

Business-level publicly available data for the PPP and EIDL programs allow us to match BWP accounts using loan recipient names and addresses. The SBA data contain the universe of federal loans for the PPP, EIDL and EIDL Advance, including their approval date and loan amount.[23]

[23] PPP data can be found at www.sba.gov/funding-programs/loans/coronavirus-relief-options/paycheck-protection-program, while EIDL data can be found at www.sba.gov/funding-programs/loans/coronavirus-relief-options/economic-injury-disaster-loans.

Since the loan data are available at the business level, we matched BWP businesses with their federal loans through a two-step process. First, the loan programs were merged into a single dataset. This entailed standardizing addresses using the US Census Bureau Geocoder and subsequently matching on names and addresses. Second, this process was repeated for the merge between BWP businesses and the federal loans. The resulting dataset provided the loan types, number, amounts, and approval dates for each BWP business.

Figure 1.7 displays the progression of the number of approved loans within Burbank for each program. As the PPP and EIDL Advance programs were established to disperse emergency funds as rapidly as possible, their counts climb quickly within the first closure period. As a more long-term financing option, the EIDL starts to pick up only after the first closure period. Though, it did eventually overtakes the PPP in the second closure period.

TABLE 1.2. Federal loan programs summary statistics

Characteristic	**No loan**	**Loan**
Number of businesses	3,587	1,226
Daily electricity use pre-pandemic (kWh)	444.5	119.4
Daily electricity use post-pandemic (kWh)	419.4	110.8
Number of business exits post-pandemic	181	61
Share of business exits post-pandemic (%)	5.7	5.2
Mean loans per business		2.0
Mean date of first loan		2020-05-06
Mean date of all loans		2020-05-17
Mean amount of first loan		121,172
Mean amount of total loan		197,504

Notes: The number of businesses are measured across the entire sample. The pre-pandemic period is assumed to be all dates before 16 March 2020, while the post-pandemic period is all dates after and including 16 March 2020. The share of business exits is standardized based on the number of businesses on 1 January 2020.

Table 1.2 provides a set of summary statistics for the combined federal loans dataset. There are approximately three times more businesses that did not receive federal assistance compared to those that did. The businesses which did not receive loans use more electricity both before and after the pandemic. It also appears as if they may suffer a larger drop in electricity use after restrictions commence. More businesses exit from the no loan group; however, the exit shares are approximately equal. Business tend to receive two loans on average, where the mean first loan is received by 6 May 2020 and amounts to around $120,000.

1.4.5. Temperature

We collect hourly temperature data from the Hollywood Burbank Airport reported through National Oceanic and Atmospheric Administration (NOAA) Local Climatology Data (LCD).[24] We then calculate hourly heating degrees representing the downward distance from 65°F. For daily analyses, temperature is meaned across a day, which is then used to calculated heating degree days (HDDs).

1.5. Business activity

In this section, we first introduce our empirical strategy and show how our approach uncovers the impact of COVID restrictions on commercial electricity use. We then move on to a presentation of our results. We begin by estimating the average change in daily electricity consumption over the four post-pandemic restriction periods. We then augment the basic model to allow temporal heterogeneity in the impacts across restriction periods, exploring how impacts vary across hours of the day. Finally, we return to the basic model but split our sample based on federal loan receipt. We estimate how federal loans may have mitigated the impacts of COVID restrictions on daily electricity consumption.

1.5.1. Empirical strategy

Our setting involves a series of events, where a population of businesses experience them simultaneously. Thus, to isolate the effect of COVID restrictions on electricity use, we adopt a two-way fixed effects model extended to a semi-dynamic panel events study (PES) framework as in Borusyak and Jaravel (2017) and Schmidheiny and Siegloch (2019). We estimate the following

[24] NOAA National Climatic Data Center, see www.ncdc.noaa.gov/cdo-web/datatools/lcd.

OLS model:

$$y_{i,t} = \sum_j \beta_j 1[r = j] + \mathbf{X}_{i,t}\gamma + \delta z_{i,m} + \alpha_{i,d,m} + \varepsilon_{i,t} \tag{1.1}$$

where $y_{i,t}$ measures electricity use in kWh for business i on date t.

Our regressors of interest are a vector of indicator variables, $1[r]$, that take a value of one during the specific COVID restriction period j and zero otherwise. We define four different restriction periods, where $j \in \{1, 3\}$ denote strict lockdowns and $j \in \{2, 4\}$ indicate periods when restrictions were relaxed. Note that the length of each period varies with the specific closing and opening orders and that periods are not industry-specific. The coefficients of interest, β_j, can be interpreted as average changes in kWh per day for Burbank businesses during the particular restriction period as compared to pre-pandemic electricity use.

The controls, $\mathbf{X}_{i,t}$, encompass local weather and Burbank COVID case numbers. Electricity use in Southern California is highly correlated with temperature, as such we have included both daily mean temperatures and HDDs. Regarding case numbers, even though individuals were mandated to shelter-in-place from mid-March 2020, it is likely many may have voluntarily avoided human interaction to reduce the risk of becoming ill. Such behavior is likely to have increased with worsening local COVID conditions. The business-specific control, $z_{i,m}$, represents month-of-year baseline electricity use and is calculated using BWP data from January 2018 to December 2019 inclusive.[25]

The term $\alpha_{i,d,m}$ represents unit and time fixed effects combinations, which nonparametrically control for observable and unobservable characteristics that vary across businesses and time periods. Thereby, the indices d and m denote day of week and month of year, respectively. The fixed effects used differ between specifications. In our base specification, we apply business, day-of-week, and month-of-year fixed effects, where the former controls for time-invariant characteristics of individual businesses, and the latter two control for weekly and seasonal patterns in use. In other specifications, we use businesses-day-of-week and business-month-of-year interaction dummies to more flexibly control for electricity usage patterns of individual businesses. Finally, we add business-weather interactions, including: business-temperature and business-HDD fixed effects. Specifications with

[25] The inclusion of baseline electricity use as well as weather and related interactions follow the empirical approaches used in Allcott and Rogers (2014), Gilbert and Graff Zivin (2014) and Novan and Smith (2018).

the full set of the fixed effects add thousands of parameters to be estimated. However, we are able to do so given the size of our sample and its high-resolution.[26]

Our approach shares important characteristics with a PES: a panel dataset of multiple units across multiple time intervals along with a set of events (Borusyak and Jaravel, 2017; Schmidheiny and Siegloch, 2019). However, in our setting all units are exposed to treatment—i.e., COVID restrictions—simultaneously. Hence, we lack variation in treatment status and event timing. These features imply, respectively, that a control group does not exist and event and calendar time are coincident. In this sense, our empirical setting also shares similarities with regression discontinuity in time (RDiT) as in Hausman and Rapson (2018). Our identifying assumptions, therefore, straddle elements from both econometric techniques.

Since our setup lacks cross-sectional variation in treatment, we rely on identification based on asymptotics in the time dimension. Assuming there are no systematic changes over time except for treatment, the difference in outcome at each event can be interpreted causally.[27]

We have identified four main threats to identification, namely: confounding factors, selection near events, time-varying treatment effects, and autocorrelation. Confounding factors are correlated with the outcome variable, while their omission threatens causal interpretation. The common prescription is to simply include them in the specification. Consequently, our main identifying assumption requires the absence of time-dependent systematic factors over the period of interest conditional on all confounding parameters.

Selection near events – also known as sorting, anticipation, adaptation or avoidance effects – is a known pitfall in regression discontinuity designs. Typically, density tests can rule out selection. However, with time as the running variable, its density is uniform rendering such tests uninformative. Similar to COVID cases, this is likely to become a larger issue the further we move from the original SIP order. Prior to LA County and a handful of others issuing closure orders on 16 March 2020, there was little warning that California would issue the SIP order three days later. Since our first restriction period begins on 16 March 2020, it likely captures all relevant anticipation effects. Later restriction periods become functions of COVID conditions. Thus, they can more easily be

[26] Additional discussion of fixed effects for estimations in the context of commercial electricity can be found in Burlig et al. (2020).

[27] This is equivalent to the absence of pre-trends and confounding simultaneous events (Hausman and Rapson, 2018; Roth, 2020).

anticipated, residents and businesses owners can more easily adapt or even avoid the restrictions. As a result, estimates further from the original SIP are of a compound effect: the causal treatment effect of interest and any unobserved selection effects.

Time-varying treatment effects violate the assumption that the treatment variable is correctly specified. One approach would be to narrow the event window; however, this would negate the ability to address seasonal confounders using a long pre-period. Neither PES, nor RDiT necessarily permit direct tests of time-varying treatment, meaning that how a treatment effect evolves over the sample window must be correctly assumed.[28] In our setting, we expect the treatment effect to vary during the analyzed periods. The nature of COVID restrictions within Burbank, however, guide our empirical specification. That is, we assume the effect on daily electricity use is constant within each restriction period.

Finally, autocorrelation can affect inference. It is typically addressed through clustered standard errors. As such, we cluster errors at the business level to account for potential arbitrary within-business correlations.

1.5.2. COVID restrictions

Figure 1.8 plots the residuals from the estimation of Equation (1.1) averaged at the weekly level along with the 95% confidence intervals. The plotted regression includes all variables except the restriction indicators, meaning that the remaining variation is a function of these same indicators and any idiosyncratic errors.

The upper panel displays the residuals from a regression with weather and baseline use controls as well as business, day-of-week and month-of-year fixed effects. The decrease in electricity use due to COVID restrictions is large and persistent. On average, a business' daily consumption falls by around 61 kWh after the initial SIP order. Mean daily consumption pre-pandemic was around 360 kWh, so this estimate represents approximately a 17% reduction in consumption.

This is quite large as illustrated by comparison to available estimates for reductions due to energy efficiency and conservation programs. For residential interventions, our estimate compares

[28] Alternatively, a difference-in-differences methodology could recover a time-varying treatment. However, in our case, we lack the control units to execute such an approach.

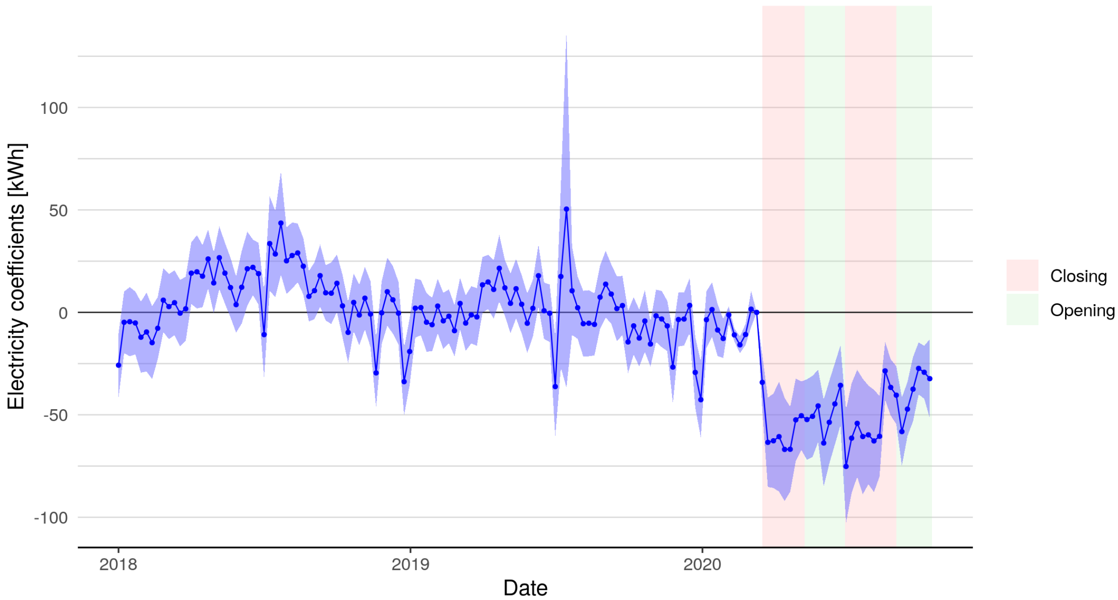
with the maximum effects found (Gillingham, Keyes and Palmer, 2018). To our knowledge, few studies on commercial interventions exist. Nonetheless, our estimate far exceeds the 3 to 5% reduction estimated by Burlig et al. (2020) proceeding energy efficiency upgrades in Californian schools.

The lower panel displays the residuals from a regression which also controls for Burbank COVID case numbers. Over time, restrictions grow dependent on COVID conditions, and thus, our variable of interest becomes increasingly correlated with cases. Assuming our specification is correct, collinearity does not bias results, though it does produce large standard errors and inefficient estimates in the relevant independent variables. As such, the results may suffer from a failure to reject a false null hypothesis or, equivalently, a type II error. This is visible in the plot as after the initial SIP order the line gradually returns to zero.

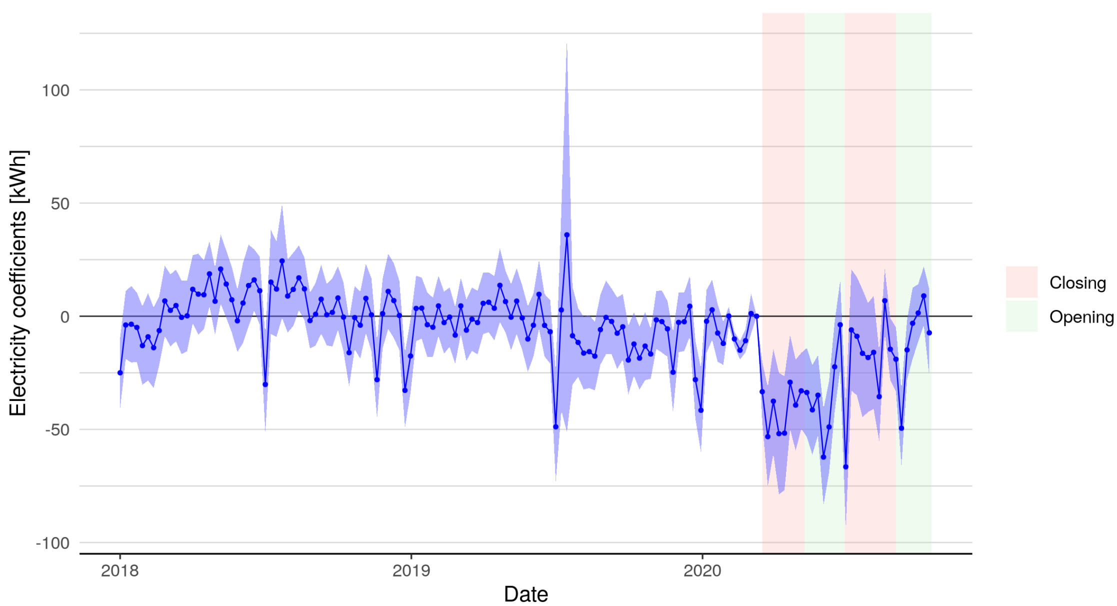
Table 1.3 reports regression estimates for Equation (1.1) and formalizes the visual results from Figure 1.8. The dependent variable in all regressions is daily electricity use measured at the business level, where industries have been limited to those identified in Section 1.4.2. The main variables of interest are event-study period indicators, i.e., Close-1, Open-1, etc., signifying intervals with either tightening or relaxing COVID restrictions, respectively. The regressions confirm statistically significant decreases in daily average commercial electricity use resulting from COVID restrictions. In columns 7 through 9, the implied daily reduction per business is between 48 and 72 kWh/day depending on the restriction period. This corresponds to between a 13 to 20% reduction on average from pre-pandemic levels. From column 3 onward, where we first include time fixed effects, these results are significant and stable across controls.

As for differences in reductions between periods, tightening and relaxing restrictions lead to economically and statistically significant changes in business activity, as measured through electricity use. As shown in Columns (7) through (9), daily commercial electricity use decreased by approximately 72, 62, 64, and 48 kWh/day on average in the Close-1, Open-1, Close-2, and Open-2 periods. These are equivalent to 20%, 17%, 18%, and 13% reductions compared to pre-pandemic levels, respectively. Periods of tightening(relaxing) restrictions correspond to higher(lower) reductions. We show this by testing the equality of the estimated restriction period coefficients.

FIGURE 1.8. Residuals for daily electricity use per business



(a)



(b)

Notes: The plots display residuals for daily electricity use per business averaged at the weekly level along with their 95% confidence intervals. Panel (a) is generated from a regression including weather and baseline use controls as well as business, day-of-week and month-of-year fixed effects. Panel (b) is generated from the same regression but with the addition of Burbank COVID case numbers. We use robust standard errors and cluster at the business level. The regression is estimated using data from January 2018 to October 2020 for all businesses within the 14 industries highlighted in the text. Red and green shaded areas represent closing and opening restriction periods within LA County.

Table 1.3. Panel event study regressions for daily electricity use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Close-1 (2020-03-16)	-78.44^{***}	-81.39^{***}	-64.70^{***}	-65.97^{***}	-66.05^{***}	-66.94^{***}	-71.40^{***}	-71.49^{***}	-71.52^{***}
	(-5.98)	(-5.93)	(-5.12)	(-5.07)	(-5.07)	(-5.11)	(-5.33)	(-5.33)	(-5.32)
Open-1 (2020-05-08)	-45.20^{***}	-49.45^{***}	-51.14^{***}	-52.16^{***}	-52.17^{***}	-61.89^{***}	-61.87^{***}	-61.87^{***}	-62.08^{***}
	(-3.70)	(-3.83)	(-3.99)	(-3.96)	(-3.96)	(-4.48)	(-4.48)	(-4.48)	(-4.48)
Close-2 (2020-06-28)	8.40	1.69	-63.50^{***}	-66.09^{***}	-65.96^{***}	-64.68^{***}	-64.00^{***}	-63.87^{***}	-63.86^{***}
	(0.38)	(0.15)	(-4.48)	(-4.46)	(-4.46)	(-4.39)	(-4.36)	(-4.36)	(-4.35)
Open-2 (2020-08-31)	30.90	11.65	-26.04^{*}	-28.40^{*}	-28.53^{*}	-43.26^{***}	-48.37^{***}	-48.50^{***}	-49.16^{***}
	(0.96)	(1.04)	(-2.27)	(-2.41)	(-2.42)	(-3.55)	(-3.88)	(-3.88)	(-3.92)
Temperature						2.97^{***}	1.55^{***}	1.55^{***}	
						(9.13)	(5.68)	(5.67)	
HDD							2.57^{***}	2.57^{***}	
							(8.46)	(8.46)	
ID FE		*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Day-of-Week FE			*X*	*X*		*X*	*X*		
Month-of-Year FE			*X*	*X*		*X*	*X*		
ID-Month Baseline				*X*	*X*	*X*	*X*	*X*	*X*
ID:Day-of-Week FE					*X*			*X*	*X*
ID:Month-of-Year FE					*X*			*X*	*X*
ID:Temp Int									*X*
ID:HDD Int									*X*
Businesses	4,813	4,813	4,813	4,546	4,544	4,546	4,546	4,544	4,544
Observations	4,402,221	4,402,221	4,402,221	4,327,915	4,327,896	4,327,915	4,327,915	4,327,896	4,327,896
R^2	0.000	0.957	0.957	0.966	0.977	0.966	0.966	0.977	0.979
Adjusted R^2	0.000	0.957	0.957	0.965	0.976	0.965	0.965	0.976	0.978

Notes: This table reports results from nine separate regressions. The dependent variable in all regressions is daily electricity use measured at the business level, where businesses are defined as name-account-address tuples. The main variables of interest are event-study period indicators signifying intervals with either tightening or relaxing COVID restrictions, respectively. We use robust standard errors and cluster at the business level. The regression is estimated using data from Jan 2018 to Oct 2020 for all businesses within the 14 industries highlighted in the text. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, *t*-statistics are in parentheses.

To assess changes between restriction periods, we first plot the restriction coefficients for daily electricity use per business along with their 95% confidence intervals in Figure 1.9. Focusing on Columns (7) through (9), the Close-to-Open transitions illustrate a slight increase in electricity use. The Open-1 and Close-2 periods, on the other hand, do not differ significantly. These visual results are confirmed through a series of Wald coefficient-equality tests as presented in Table 1.C.1 in Appendix 1.C. We reject the the null hypothesis of equality for the Close-1-to-Open-1 and the Close-2-to-Open-2 transitions at the 95% level. For the Open-1-to-Close-2 transition, we fail to reject it as soon as temperature variables are included. Thus, the two instances where COVID restrictions were relaxed led to statistically significant increases in business activity, while the single instance of tightening restrictions essentially maintained the status quo.

We find that our results for daily electricity use are robust to an alternative definition of businesses. Details can be found in Appendix 1.D.2.

We now turn to a brief investigation of hourly electricity use outcomes. A key advantage of such high-frequency data is that it allows us to estimate not only the extent of the reduction but also when during the day it occurred. To examine how the impact of COVID restrictions vary across hours of the day, we estimate the model in Equation (1.1) separately for each hour. Our dependent variable is now $y_{i,t}^h$ symbolizing the electricity consumed by business i during hour h on date t. We, therefore, obtain 24 point estimates for each restriction period coefficient $\beta_j^h \; \forall \; j \in [1, 4]$.

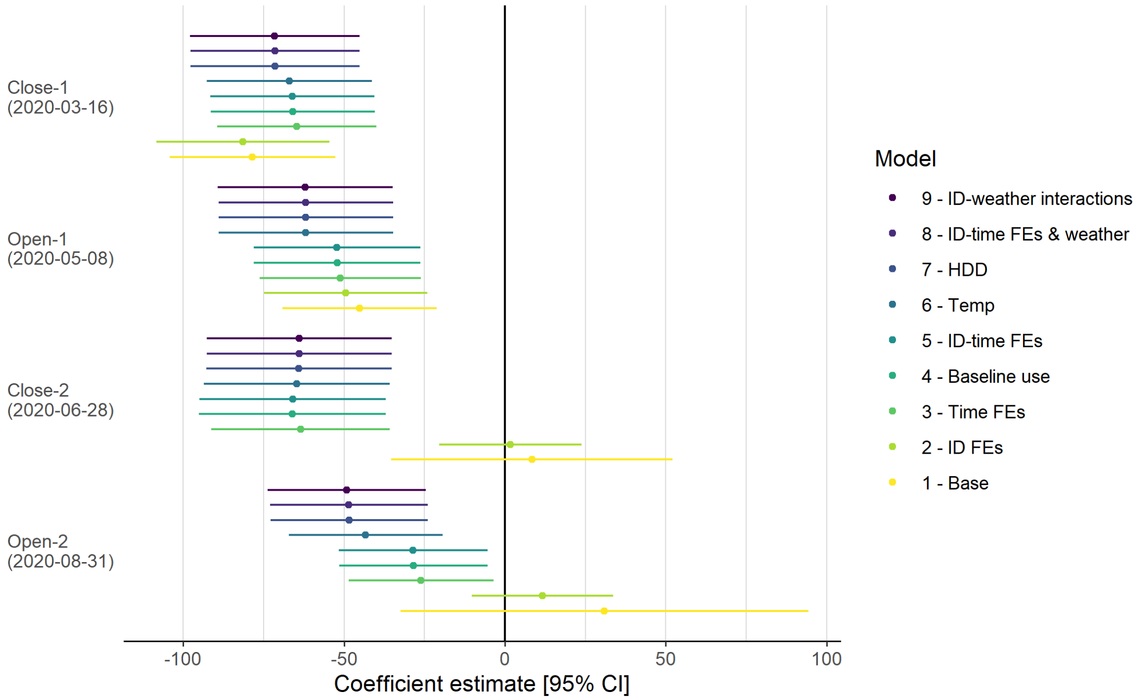
Figure 1.10 displays the hourly distribution of electricity use estimators and their 99% confidence intervals by restriction period. It reveals the mirror image of the typical commercial electricity distribution.[29] That is, the greatest decreases are in the mid-day hours, corresponding to the typical working day. Smaller, but statistically significant, decreases occur across all other hours.

On average, businesses suffered substantial decreases in hourly electricity use during typical business hours. For the Close-1 through to the Close-2 restriction period, hourly electricity use decreased by more than 3 kWh each hour between 9 AM and 8 PM.[30] These decreases persisted until the Close-2 period when there was a small uptick in midday electricity use. The increase

[29] A typical commercial hourly distribution of electricity consumption exhibits low overnight, morning and evening use. These low periods surround a global maximum which builds through the morning and lunchtime hours and peaks in the mid-afternoon.

[30] These results are difficult to compare to the effects of energy efficiency and conservation programs. Related papers typically do not report hourly effects, and those that do lack results in terms of a pre-intervention

FIGURE 1.9. Restriction coefficients for daily electricity use per business



Notes: The plot displays restriction coefficients for daily electricity use per business along with their 95% confidence intervals from Table 1.3. It is generated from a regression including weather and baseline use controls as well as business, day-of-week and month-of-year fixed effects. We use robust standard errors and cluster at the business level. The regression is estimated using data from January 2018 to October 2020 for all businesses within the 14 industries highlighted in the text.

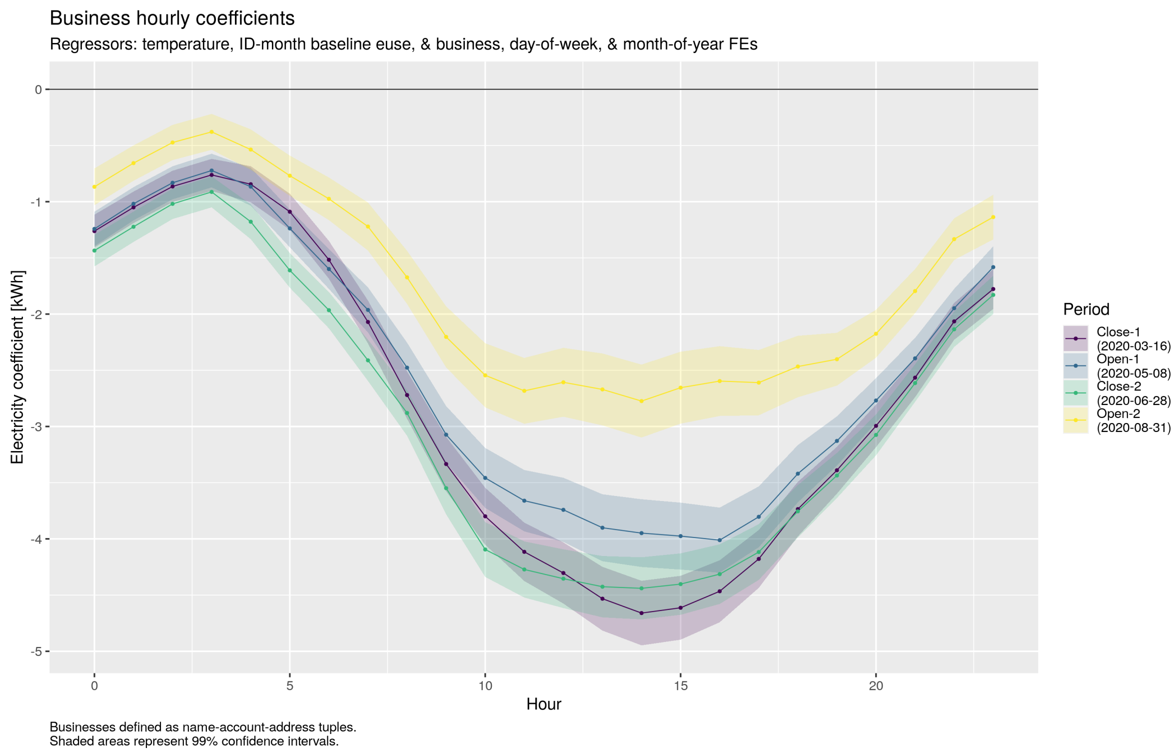
broadly corresponds to the implementation of the Blueprint for a Safer Economy, where non-essential businesses were permitted to reopen with modifications. This perhaps provides support for the change in hourly patterns of electricity use across restriction periods.

1.5.3. Federal loans

We now turn to the question of how the receipt of federal loans relate to business response to COVID restrictions. To answer it, we estimate Equation (1.1) separately for firms that did and did not receive a federal loan.

baseline. Nevertheless, two papers reviewing separate residential AC programs in California produce hourly estimates in levels. Novan and Smith (2018) find a maximum reduction of -0.14 kWh between April to October, and Boomhower and Davis (2019) find a maximum reduction of -0.31 kWh between July and August.

FIGURE 1.10. Restriction coefficients for hourly electricity use per business



Notes: The plots display coefficients of the four restriction periods for hourly electricity use per business along with their 99% confidence intervals. The coefficients are generated from a regression including weather and baseline use controls as well as business, day-of-week and month-of-year fixed effects. We use robust standard errors and cluster at the business level. The regression is estimated using data from Jan 2018 to Oct 2020 for all businesses within the 14 industries highlighted in the text.

One drawback with this approach is that the application for for a federal loan is a decision made by individual businesses, and this choice may be systematically correlated with determinants of electricity use. As shown in Table 1.4, we find measurable differences in baseline observables differentiated by federal loan receipt. Those receiving loans are systematically smaller and more labor intensive. This emphasizes the interpretation of our results as correlational and makes clear that differences in the response to COVID restrictions may be due to other characteristics that are systematically correlated with the receipt of federal loans. As such, we view this exercise as a first step in providing suggestive empirical evidence on the mitigating effects of federal loans.[31]

[31] The analysis in this section eventually requires that we address selection into treatment in order to produce estimates with underlying causal interpretations. One possibility is to match businesses on electricity use profiles and other characteristics (Cicala, 2015; Ferraro and Miranda, 2017). Alternatively, we could attempt a synthetic control

Table 1.4. Average characteristics of businesses by loan receipt

Characteristic	No loan	Loan	Difference
Daily Electricity Use (kWh)	448.0	120.6	327.4***
	(3,312.3)	(277.7)	[149.21]
Accommodation and Food Services (%)	9.5	10.5	−1.1
	(29.3)	(30.7)	[−1.06]
Administrative and Support and Waste Management and Remediation Services (%)	1.2	2.1	−0.9
	(11.1)	(14.4)	[−1.87]
Arts, Entertainment, and Recreation (%)	2.3	2.9	−0.5
	(15.1)	(16.7)	[−1.00]
Construction (%)	3.0	3.6	−0.6
	(17.1)	(18.7)	[−1.01]
Educational Services (%)	2.4	2.5	−0.1
	(15.4)	(15.7)	[−0.17]
Finance and Insurance (%)	4.4	2.8	1.6**
	(20.6)	(16.5)	[2.77]
Health Care and Social Assistance (%)	8.3	14.2	−5.8***
	(27.6)	(34.9)	[−5.22]
Information (%)	19.9	10.1	9.7***
	(39.9)	(30.2)	[8.75]
Manufacturing (%)	7.8	7.9	−0.1
	(26.9)	(27.0)	[−0.12]
Other Services (except Public Administration) (%)	13.8	15.6	−1.8
	(34.5)	(36.3)	[−1.49]
Professional, Scientific, and Technical Services (%)	5.4	6.6	−1.2
	(22.5)	(24.8)	[−1.50]
Retail Trade (%)	15.7	15.8	−0.1
	(36.4)	(36.5)	[−0.08]
Transportation and Warehousing (%)	2.9	1.4	1.5***
	(16.7)	(11.5)	[3.47]
Wholesale Trade (%)	3.3	4.0	−0.6
	(18.0)	(19.5)	[−0.98]
Number of Observations	2,322,551	845,643	
Number of Businesses	3,361	1,185	

Notes: This table displays average characteristics by loan receipt prior to 1 January 2020. Standard deviations are in parentheses, with t-statistics of the difference between 'no loan' and 'loan' businesses in brackets where *** p<0.001; ** p<0.01; * p<0.05. Each row is a separate calculation, and is not conditional on the other variables reported here.

Figure 1.11 is the companion plot to Figure 1.8. It illustrates the residuals from the estimation of Equation (1.1) averaged at the weekly level along with the 95% confidence intervals. The sample

with "essential" businesses comprising the control group (Abadie, Diamond and Hainmueller, 2010). Or finally, we could use machine learning to produce business-specific counterfactuals (Burlig et al., 2020).

FIGURE 1.11. Residuals for daily electricity use per business by loan receipt

Notes: The plot displays residuals for daily electricity use per business averaged at the weekly level along with their 95% confidence intervals. The residuals are from two separate regressions with the first based on the sample of businesses receiving a federal loan, and the second not. The regressions include weather and baseline use controls as well as business, day-of-week and month-of-year fixed effects. We use robust standard errors and cluster at the business level. The regression is estimated using data from January 2018 to October 2020 for all businesses within the 14 industries highlighted in the text. Red and green shaded areas represent closing and opening restriction periods within LA County.

is split based on loan receipt. After the initial SIP order, electricity use for both groups dramatically decrease and their confidence intervals are no longer overlapping. Notably, those businesses that received a loan decrease in levels far less than those that did not. This is true for the entire post-pandemic period available. On average, daily consumption for businesses receiving loans falls by around 22 kWh/day, while for those without loans it decreases by around 75 kWh/day. Given the systematic differences between groups, it is challenging to compare these effects.

Table 1.5 formalizes the visual results in Figure 1.11. It shows how the estimates for Equation (1.1) change with loan receipt status. The regressions confirm statistically significant decreases in daily average commercial electricity use in both groups. The response is correlated with federal

Table 1.5. Panel event study regressions for daily electricity use by loan receipt

	All Data		**No loan**		**Loan**	
	(1)	(2)	(3)	(4)	(5)	(6)
Close-1 (2020-03-16)	-64.76^{***}	-70.05^{***}	-80.38^{***}	-86.54^{***}	-24.12^{***}	-27.05^{***}
	(-5.13)	(-5.38)	(-4.61)	(-4.82)	(-9.69)	(-10.69)
Open-1 (2020-05-08)	-51.29^{***}	-60.78^{***}	-64.99^{***}	-76.47^{***}	-15.49^{***}	-19.59^{***}
	(-4.01)	(-4.53)	(-3.68)	(-4.13)	(-6.63)	(-8.04)
Close-2 (2020-06-28)	-67.84^{***}	-65.79^{***}	-84.03^{***}	-81.60^{***}	-24.03^{***}	-23.03^{***}
	(-4.58)	(-4.48)	(-4.13)	(-4.04)	(-9.10)	(-8.80)
Open-2 (2020-08-31)	-26.16^{*}	-45.60^{***}	-32.26^{*}	-55.48^{***}	-9.86^{***}	-19.02^{***}
	(-2.28)	(-3.75)	(-2.04)	(-3.32)	(-4.25)	(-7.71)
Temperature		1.52^{***}		1.91^{***}		0.46^{***}
		(5.69)		(5.24)		(7.23)
HDD		2.51^{***}		2.90^{***}		1.45^{***}
		(8.49)		(7.20)		(17.30)
ID FE	*X*	*X*	*X*	*X*	*X*	*X*
Day-of-Week FE	*X*	*X*	*X*	*X*	*X*	*X*
Month-of-Year FE	*X*	*X*	*X*	*X*	*X*	*X*
Businesses	4,813	4,813	3,587	3,587	1,226	1,226
Observations	4,402,226	4,402,226	3,221,133	3,221,133	1,181,093	1,181,093
R^2	0.92	0.92	0.92	0.92	0.90	0.90
Adjusted R^2	0.92	0.92	0.92	0.92	0.90	0.90

Notes: This table reports results from six separate regressions. The dependent variable in all regressions is daily electricity use measured at the business level, where businesses are defined as name-account-address tuples. The main variables of interest are event-study period indicators signifying intervals with either tightening or relaxing COVID restrictions, respectively. The sample for Columns (1) and (2) contains all businesses and replicate Columns (4) and (7) from Table 1.3. The sample for Columns (3) and (4) is limited to only those businesses not receiving a federal loan, while that for Columns (5) and (6) is limited to those that do. We use robust standard errors and cluster at the business level. The regression is estimated using data from Jan 2018 to Oct 2020 for all businesses within the 14 industries highlighted in the text. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, *t*-statistics are in parentheses.

loans, as those receiving them experience smaller decreases in levels. Those receiving loans experience decreases between 19 and 27 kWh/day, while those without loans see decreases of between

55 and 86 kWh/day.[32] However, these results are confounded with other factors and cannot be interpreted causally.

1.6. Business exits

In this section, we investigate how the closure orders impacted business exits, where we proxy exits using electricity account terminations. We also assess the extent to which federal loans are systematically correlated with the probability of exit. We first introduce our empirical strategy and then presentation our results.

1.6.1. Empirical strategy

We propose two empirical approaches to estimate the effect of closure orders on industry exit: an event study framework and a survival analysis. In the event study approach, we replicate the approach discussed in Section 1.5.1, except we replace the dependent variable with net account terminations. This allows us to evaluate how different restriction periods impact exit relative to similar pre-pandemic time periods. Second, we perform a survival analysis, which investigates the probability of exit conditional on remaining in the sample.

To operationalize the event study framework, we estimate the following regression:

$$y_{i,z,t} = \sum_{j} \beta_j 1[r = j] + \mathbf{X}_{i,z,t}\boldsymbol{\gamma} + \alpha_{i,z,m} + \varepsilon_{i,z,t}, \tag{1.2}$$

where $y_{i,z,t}$ represents the number of open electricity accounts for a given industry i and zip code z on week t. Industries are defined by NAICS-2 classification and there are five standard zip codes within the City of Burbank. The indicator functions, $1[r]$, represent restriction periods $j \in \{1, \ldots, 4\}$, while the coefficients of interest, β_j, can be interpreted as the average net account closings per industry-zip during the particular restriction period. The controls, $\mathbf{X}_{i,z,t}$, represent weekly mean temperature and count of HDDs.

[32] The results are more nuanced when considering the effects compared to baseline. Percent reductions for those receiving loans are lower compared to those that did not only during the Open-2 period. This suggests that the loans provided only short-term relief and were ineffective in the long-run. However, such results should be treated with caution as the supports for the two groups clearly do not overlap.

The term $\alpha_{i,z,m}$ represents unit and time fixed effects combinations, where m denotes month of year. The fixed effects used differ between specifications. In our base specification, we apply industry-zip, month-of-year fixed effects, where the former controls for time-invariant characteristics of individual industry-zip groups and the latter for seasonal patterns in exit. In other specifications, we use industry-zip-month-of-year interaction dummies to more flexibly control for exit patterns of specific regional industries. Finally, we add industry-zip-weather interactions, including: industry-zip-temperature, and industry-zip-HDD fixed effects.

Our approach to the survival analysis is closely linked to binary response models for grouped duration data (see e.g., Singer and Willet, 1993; Sueyoshi, 1995). A similar approach has recently been used to study water shocks on the Nile (Chaney, 2013) and gas wells in the Bakken (Lade and Rudik, 2020). In our set-up we define the dependent variable as an indicator set equal to zero if business i on date t does not exit and one if it does. Businesses are then dropped from the panel after their exit date. We estimate the following regression:

$$y_{i,t} = \sum_j \beta_j 1[r = j] + \alpha_i + \varepsilon_{i,t} \tag{1.3}$$

where $y_{i,t}$ is the exit indicator variable for business i on day t. Given our setup, the coefficients of interest, β_r, can be interpreted as the change in probability that a business exits during the specific restriction period compared to pre-pandemic, conditional on remaining in the sample on a given day. The α_i term represents business fixed effects. We restrict our sample to dates in 2020 only.

The identifying assumptions for both approaches mirror those outlined in Section 1.5.1 above.

1.6.2. Results

Table 1.7 presents results from the estimation of Equation (1.2). The dependent variable in all regressions is electricity account numbers measured at the industry-zip level, where industries have been limited to those identified in Section 1.4.2. The main variables of interest are event-study period indicators, i.e., Close-1, Open-1, etc., signifying intervals with either tightening or relaxing COVID restrictions, respectively. Their coefficients should be interpreted as cumulative business exits. A central result is that COVID restrictions induced industry exit. Relative to pre-pandemic years, we find that by the end of mid-October 2020 around 2 more businesses than normal closed their operations. These results are stable to the inclusion of more flexible time and weather fixed effects.

Table 1.6 presents results from our survival analysis estimations based on Equation (1.3). Coefficients are reported as percentage points. In order to compare results across periods, we standardize them by multiplying each coefficient by its period length. The results are the percentages reported in square brackets. They represent the probability of exit during the respective period, conditional on having not already exited.

Column (1) performs the survival analysis regression for all businesses in our sample. Its results highlights that COVID restrictions increased the probability of exit. Moreover, the probability increases over sequential periods from Close-1 through to Close-2. It peaks during the Close-2 period, where businesses experience around a 3.5% probability of exit compared to the period immediately preceding the initial SIP orders. While still quite high, the Open-2 period sees the probability decreases to 2.3%, suggesting that relaxed restrictions attenuated the rate of exit.

Columns (2) and (3) report separate regressions based on loan receipt. The former contains only those businesses that did not receive a loan, while the latter includes those that did. The two regressions return almost identical results for each restriction period. However, we find that the receipt of a loan is correlated with a substantial reduction in the probability of exit during the first restriction period. Thus, federal loans appear to reduce the likelihood of exit initially, though this effect attenuates quite rapidly.[33]

1.7. Conclusion

In this paper, we study how the pandemic and its public policy responses have impacted businesses. Using high-resolution electricity data from Burbank, California, we estimate how business activity, exit and survival change based on the ratcheting into and out of COVID restrictions. We

[33] Notably, for our framework to identify the effect of federal loans on the probability of exit, the error terms must be uncorrelated with loan receipt conditional on covariates. However, loan receipt is not randomly assigned. Therefore, we cannot interpret the differences between estimated parameters in columns 2 and 3 as causal effects as there may be unobserved factors driving federal loan applications confounding the comparison. Due to this selection bias, our results associated with these columns should be interpreted as correlations.

TABLE 1.6. Survival analysis regressions for the probability of exit by loan receipt

	All Data	**No loan**	**Loan**
	(1)	(2)	(3)
Close-1 (2020-03-16)	0.00013***	0.00016***	0.00002
52 days	(4.59)	(4.44)	(1.18)
	[0.68%]	[0.83%]	[0.10%]
Open-1 (2020-05-08)	0.00032***	0.00032***	0.00031***
50 days	(7.80)	(6.74)	(3.94)
	[1.60%]	[1.60%]	[1.55%]
Close-2 (2020-06-28)	0.00055***	0.00055***	0.00055***
63 days	(12.05)	(10.35)	(6.16)
	[3.47%]	[3.47%]	[3.47%]
Open-2 (2020-08-31)	0.00052***	0.00052***	0.00051***
45 days	(11.85)	(10.24)	(5.98)
	[2.34%]	[2.34%]	[2.30%]
ID FE	X	X	X
Businesses	4,602	3,387	1,215
Observations	1,234,032	898,582	335,450
R^2	0.02849	0.03278	0.01278
Adjusted R^2	0.02485	0.02912	0.00918

Notes: This table reports results from three separate regressions. The dependent variable in all regressions is a dummy variable set to zero if business i does not exit on date t and one if it does, where businesses are defined as name-account-address tuples. The main variables of interest are event-study period indicators signifying intervals with either tightening or relaxing COVID restrictions, respectively. The sample for column 1 contains all businesses, while the samples for columns 2 and 3 are limited to businesses not receiving a federal loan and those receiving one, respectively. We use robust standard errors and cluster at the business level. The regression is estimated using data from January to October 2020 for all businesses within the 14 industries highlighted in the text. Significance is represented as *** for $p<0.001$, ** for $p<0.01$, and * for $p<0.05$; while, t-statistics are in parentheses and period probabilities are in square brackets.

Table 1.7. Panel event study regressions for electricity account numbers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Close-1 (2020-03-16)	-0.62^{***}	-0.47^{***}	-0.47	-0.45^{***}	-0.47^{***}	-0.46	-0.46
	(0.09)	(0.10)	(0.33)	(0.10)	(0.10)	(0.33)	(0.33)
Open-1 (2020-05-08)	-1.00^{***}	-1.05^{***}	-1.05^{**}	-0.96^{***}	-1.00^{***}	-1.00^{**}	-1.00^{**}
	(0.09)	(0.11)	(0.36)	(0.11)	(0.11)	(0.37)	(0.37)
Close-2 (2020-06-28)	-1.54^{***}	-1.83^{***}	-1.84^{***}	-1.82^{***}	-1.83^{***}	-1.83^{***}	-1.83^{***}
	(0.08)	(0.09)	(0.36)	(0.09)	(0.09)	(0.36)	(0.36)
Open-2 (2020-08-31)	-2.18^{***}	-2.43^{***}	-2.45^{***}	-2.28^{***}	-2.26^{***}	-2.28^{***}	-2.28^{***}
	(0.09)	(0.10)	(0.38)	(0.11)	(0.11)	(0.36)	(0.36)
Temp				-0.03^{***}	-0.04^{***}	-0.04^{***}	
				(0.01)	(0.01)	(0.01)	
HDD					0.03	0.03^{***}	
					(0.02)	(0.01)	
Industry-Zip FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Month-of-Year FE		*X*		*X*	*X*		
IZ:Month-of-Year FE			*X*			*X*	*X*
IZ:Temp Int							*X*
IZ:HDD Int							*X*
Industry-Zips	68	68	68	68	68	68	68
Observations	9,820	9,820	9,820	9,820	9,820	9,820	9,820
R^2	0.09	0.10	1.00	0.10	0.10	1.00	1.00
Adjusted R^2	0.08	0.09	1.00	0.09	0.09	1.00	1.00

Notes: This table reports results from seven separate regressions. The dependent variable in all regressions is electricity account numbers measured at the industry-zip level, where the 14 industries and 5 standard zip codes are defined in the text. The main variables of interest are event-study period indicators signifying intervals with either tightening or relaxing COVID restrictions, respectively. We use robust standard errors and cluster at the industry-zip level. The regression is estimated using data from January 2018 to October 2020. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, standard errors are in parentheses.

also estimate correlations between business activity and federal loan programs, specifically the PPP and EIDL.

We find statistically significant decreases in daily and hourly average commercial electricity use resulting from COVID restrictions. Business closure orders in Burbank led to, on average, 64 to 71 kWh reduction in daily business-level electricity use, which amounts to between 18% to 20% of pre-pandemic electricity usage. Partial re-openings experienced in the late spring and early autumn also exhibited decreases but of smaller magnitude, 49 to 62 kWh or 13% to 17%, on average, relative to the same business over the same time period in pre-pandemic years. While electricity reductions were present across all hours of the day, the largest drops occurred during extended business hours between 9 AM and 8 PM.

COVID-19 restrictions had increasingly adverse effects on business status. Relative to pre-pandemic years, we find that by the end of mid-October 2020 around 2 more businesses per industry-zip exited than normal. Moreover, the probability of exit increased between 1.6% and 3.5% between May and October 2020, relative to pre-pandemic levels. This suggests that that the pandemic in conjunction with public health orders caused significant and harmful effects across both the intensive and extensive margins of business operations.

We also note that federal loan receipt correlates with smaller decreases in electricity use. This is true for the entire set of restriction periods available. Federal loan receipt also relates to a smaller decrease in survival probability during the initial closure period. However, the effect of federal loans on survival appears to attenuate quite rapidly.

Given the unique nature of the pandemic and the scale and scope of the resultant federal assistance, it is important to understand the welfare impacts of these events, including their impact on the business community. This applies both in retrospect, as a method of assessing the impacts of the pandemic and the effectiveness of the responses, as well as serving as a guide to future federal loan and grant programs. On the evidence presented here to date, non-essential business closures lead to businesses reducing activity and exiting the market. These effects persist even in periods when restrictions are relaxed. Federal loan programs were unable to prevent these adverse effects; however, they do seem to mitigate them.

Going forward, we intend to extend our analysis in a number of ways. First, we plan to study heterogeneity across industries to establish whether the pandemic and the responses affected industries differently. This requires better business-industry mappings. Second, our analyses of federal loans, at present, suffers from selection bias. This is clear from the divergent balance statistics reported in Table 1.4. Identification requires that we compare loan and no loan groups with overlapping support. This suggests performing a matching exercise in conjunction with a DD design (Cicala, 2015; Ferraro and Miranda, 2017). Alternatively, we could develop a synthetic control composed of essential businesses (Abadie, Diamond and Hainmueller, 2010) and/or use machine learning to generate business-specific counterfactuals of post-SIP consumption (Burlig et al., 2020).

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Appendix

1.A. Public health orders

Table 1.A.1. Major state and county government actions related to COVID-19 health and public safety

Action	**Govt**	**Date**	**Direction**	**Description**
State of Emergency Proclamation	CA	2020-03-04	N/A	Governor Newsom declared a State of Emergency to make additional resources available, formalize emergency actions underway across multiple state agencies and departments, and help the state prepare for broader spread of COVID-19.
County Public Health Order (Close-1)	LA	2020-03-16	Closing	County Health Officer Davis issued an Order prohibiting events and gatherings of 50 or more and requiring the closure of certain non-essential businesses, including: bars and nightclubs that do not serve food, gyms, fitness centers, movie and performance theaters, bowling alleys and arcades.
County Public Health Order	LA	2020-03-19	Closing	County Health Officer Davis issued an updated Order prohibiting all public and private gatherings of 10 or more and requiring the closure of additional non-essential businesses, including: retailers and indoor shopping centers, regardless of whether they contain essential businesses.
Executive Order N-33-20	CA	2020-03-19	Closing	Governor Newsom and State Public Health Officer Dr. Angell issued a shelter-in-place order to establish consistency across the state in order to slow the spread of COVID-19.
County Public Health Order	LA	2020-03-21	Closing	County Health Officer Davis issued an updated Order to comply with Executive Order N-33-20, wherein the State Public Health Officer ordered all individuals living in the State of California to stay home or at their place of residence, except as needed to maintain continuity of operations of the federal critical infrastructure sectors. The Order prohibits all indoor and outdoor public and private gatherings and events and requires the closure of all businesses unless defined as essential.
Resilience Roadmap	CA	2020-04-14	N/A	Governor Newsom unveiled six key indicators guiding how and when to modify the statewide stay-at-home order (i.e. Executive Order N-33-20): (1) the ability to monitor and protect communities through testing, contact tracing, isolating, and supporting those who are positive or exposed; (2) the ability to prevent infection in people who are at risk for more severe COVID-19; (3) the ability of the hospital and health systems to handle surges; (4) the ability to develop therapeutics to meet the demand; (5) the ability for businesses, schools, and child care facilities to support physical distancing; and, (6) the ability to determine when to re-institute certain measures, if necessary. The Governor did not confirm a precise timeline for modifying the stay-at-home order, but rather, that these six indicators will serve as the framework for making that decision.
Executive Order N-60-20	CA	2020-05-04	N/A	Governor Newsom issued an executive order directing the State Public Health Officer to establish criteria to determine whether and how local health officers may implement public health measures less restrictive than the statewide public health directives.

Action	Govt	Date	Direction	Description
State Public Health Order	CA	2020-05-08	Opening	State Public Health Officer Dr. Angell issued an order for the gradual movement of the entire state from Stage 1 to Stage 2 of California's Pandemic Resilience Roadmap. Gradual movement into Stage 2 is intended to reintroduce activities and sectors in a phased manner and with necessary modifications. However, a local health jurisdiction may implement or continue more restrictive public health measures if the jurisdiction's Local Health Officer believes conditions in that jurisdiction warrant it.
County Public Health Order (Open-1)	LA	2020-05-08	Opening	County Health Officer Davis issued an updated Order to allow certain types of non-essential businesses to reopen. Subsequent Orders permitting a phased reopening of additional non-essential businesses continued throughout May and June.
State Public Health Order (Close-2)	CA	2020-06-28	Closing	Governor Newsom and the California Department of Public Health released guidance on the closure of bars for counties on the County Monitoring List. Counties which have been on the List for 14 days or more are required to immediately close bars, including Los Angeles County. This was followed by a series Resilience Roadmap guidelines at the State level for the closure of non-essential businesses and subsequent orders at the LA County level over July and August.
Blueprint for a Safer Economy	CA	2020-08-28	N/A	Governor Newsom unveiled the Blueprint for a Safer Economy, a statewide, stringent and slow plan for living with COVID-19 for the long haul. The plan imposes risk-based criteria on tightening and loosening COVID-19 allowable activities and expands the length of time between changes to assess how any movement affects the trajectory of the disease. This new framework modifies the state-wide stay-at-home order (N-33-20) to apply at the county-level based on risk-based criteria. Moreover, it makes a number of changes to the state's previous resilience roadmap. Notably, the plan commences a more nuanced way of allowing activity: instead of open vs. closed, sectors can be partially opened and progressively add to their operations as disease transmission decreases.
State Public Health Order (Open-2)	CA	2020-08-31	Opening	Acting State Public Health Officer Dr. Pan issued a state-wide order updating the framework for reopening under the Blueprint for a Safer Economy. Pursuant to this framework, all local health jurisdictions in the state may reopen specified sectors according to their respective county's Tier. This was followed by a series of phased reopenings with modifications at the State and County level over September to November.

1.B. Federal loans

TABLE 1.B.1. Major federal government actions related to COVID-19 economic assistance

Event	Actor	Date	Description
EIDL availability	Congress	2020-03-06	The Coronavirus Preparedness and Response Supplemental Appropriations Act specified the coronavirus as a disaster under the EIDL program; thus, economic injury from the coronavirus became an eligible EIDL expense and loans for such purposes were made available immediately from existing appropriations.
CARES Act	Congress	2020-03-27	The Coronavirus Aid, Relief, and Economic Security (CARES) Act created the PPP, under the SBA's Section 7(a) lending program. The Act appropriated $349 billion for PPP loan guarantees, $10 billion for Emergency EIDL Advance Payment grants, and $562 million for EIDL loans.
EIDL Advance availability	SBA	2020-03-30	The SBA updated its website to allow COVID-19-related EIDL applicants an option to request an Emergency EIDL Advance Payment grant.
PPP availability	SBA	2020-04-03	The SBA began accepting PPP loan applications.
PPP, EIDL and EIDL Advance closure	SBA	2020-04-15	Within 12 days, the SBA neared its $349 billion authorization limit for Section 7(a) lending which included the PPP. It was also approaching its disaster loan assistance credit subsidy limit. Thus, the SBA stopped accepting new PPP, as well as COVID-19-related EIDL and EIDL Advance loan applications.
Enhancement Act	Congress	2020-04-24	The Paycheck Protection Program and Health Care Enhancement (Enhancement) Act increased the SBA's Section 7(a) loan authorization limit from $349 billion to $659 billion, and appropriated $321 billion to support that level of lending. The Enhancement Act also appropriated an additional $10 billion for Emergency EIDL Advance grants and $50 billion for EIDL loans.
PPP, EIDL and EIDL Advance availability	SBA	2020-04-27	The SBA resumed the acceptance of new PPP, EIDL and EIDL Advance loan applications.
EIDL Advance closure	SBA	2020-07-11	The SBA announced it had stopped accepting EIDL Advance grant applications as the program had reached its authorization limit of $20 billion.
Additional appropriations fail	Congress	2020-07-27	The Continuing Small Business Recovery and Paycheck Protection Program Act was introduced in the Senate and, if passed, would have increased the PPP authorization amount from $659 billion to $749 billion. To accomplish this it would have rescinded $100 billion from the SBA's business loan program account and appropriated an additional $190 billion for the cost of PPP and PPP second draw loans resulting in $90 billion of new appropriations.

Event	Actor	Date	Description
PPP closure	SBA	2020-08-08	The PPP closed to new applications as stipulated by Congress through the Enhancement Act.

1.C. Wald coefficient-equality tests

The Wald coefficient-equality test is used to determine if two coefficients within the same regression are equal. Essentially, it answers the question of whether two different coefficients have the same statistical effect on our independent variable.

It is calculated as the ratio of the difference over the standard error of that difference:

$$W = \frac{\beta_r - \beta_s}{\sqrt{\sigma_r^2 + \sigma_s^2 - 2\sigma_{rs}}}$$

where $\beta_i \ \forall \ i \in \{r, s\}$ are the restriction coefficients, and σ_i^2 and $\sigma_{i,-i}$ are the coefficient variances and covariance, respectively. The Wald statistic, W, can be treated as a t-statistic from a normal distribution. Therefore, W-statistics with a value greater than the absolute value 1.96 are significant at the 95% level.

The results of the tests confirm align with our prior expectations. From Table 1.C.1, we fail to reject the null hypothesis that the Close-1 and Close-2 restriction periods are statistically different across most Columns. This, however, is not the case when comparing Close-1 to either of the two Open periods. We reject the null hypothesis and find that Close-1 is statistically different from both Open-1 and Open-2 across all Columns. We find Open-1 and Close-2 are statistically similar, but only for the most parsimonious Columns. Otherwise, the remains restriction periods are statistically different from one another.

Table 1.C.1. Wald coefficient-equality tests for restriction coefficients from Table 1.3

Column	Close-1 = Open-1	Close-1 = Close-2	Close-1 = Open-2	Open-1 = Close-2	Open-1 = Open-2	Close-2 = Open-2
(1)	90.89^{***}	15.23^{***}	10.48^{**}	6.18^{*}	5.29^{*}	2.93
	$(2.34e-21)$	$(9.66e-05)$	$(1.21e-03)$	$(1.29e-02)$	$(2.14e-02)$	$(8.73e-02)$
(2)	90.99^{***}	74.27^{***}	46.64^{***}	52.23^{***}	29.04^{***}	4.14^{*}
	$(2.22e-21)$	$(9.13e-18)$	$(9.58e-12)$	$(5.70e-13)$	$(7.43e-08)$	$(4.19e-02)$
(3)	24.87^{***}	0.08	22.53^{***}	18.63^{***}	15.02^{***}	32.45^{***}
	$(6.34e-07)$	$(7.75e-01)$	$(2.13e-06)$	$(1.62e-05)$	$(1.08e-04)$	$(1.30e-08)$
(4)	23.22^{***}	0.00	19.90^{***}	20.34^{***}	12.63^{***}	28.75^{***}
	$(1.49e-06)$	$(9.78e-01)$	$(8.38e-06)$	$(6.64e-06)$	$(3.84e-04)$	$(8.65e-08)$
(5)	23.37^{***}	0.00	19.89^{***}	20.06^{***}	12.59^{***}	28.70^{***}
	$(1.38e-06)$	$(9.83e-01)$	$(8.39e-06)$	$(7.70e-06)$	$(3.91e-04)$	$(8.89e-08)$
(6)	4.13^{*}	0.26	10.78^{**}	0.90	8.92^{**}	15.41^{***}
	$(4.23e-02)$	$(6.10e-01)$	$(1.03e-03)$	$(3.44e-01)$	$(2.83e-03)$	$(8.76e-05)$
(7)	15.51^{***}	2.96	10.25^{**}	0.53	5.04^{*}	9.49^{**}
	$(8.32e-05)$	$(8.52e-02)$	$(1.38e-03)$	$(4.68e-01)$	$(2.48e-02)$	$(2.08e-03)$
(8)	15.74^{***}	3.14	10.24^{**}	0.46	4.99^{*}	9.33^{**}
	$(7.36e-05)$	$(7.64e-02)$	$(1.38e-03)$	$(4.95e-01)$	$(2.55e-02)$	$(2.27e-03)$
(9)	15.41^{***}	3.18	9.92^{**}	0.37	4.75^{*}	8.90^{**}
	$(8.78e-05)$	$(7.45e-02)$	$(1.64e-03)$	$(5.42e-01)$	$(2.93e-02)$	$(2.87e-03)$

Notes: This table reports Wald coefficient-equality tests based on results from nine separate regressions originally reported in Table 1.3. The dependent variable in all regressions is daily electricity use measured at the business level, where businesses are defined as name-account-address tuples. The main variables of interest, and those used in the Wald tests, are event-study period indicators signifying intervals with either tightening or relaxing COVID restrictions, respectively. Standard errors are robust to heteroskedasticity and clustering at the business level. The regressions are estimated using data from January 2018 to October 2020 inclusive for all businesses within the 14 industries highlighted in the text. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, F-statistics are without parentheses and p-values $Pr(> F)$ are within them.

1.D. Robustness checks

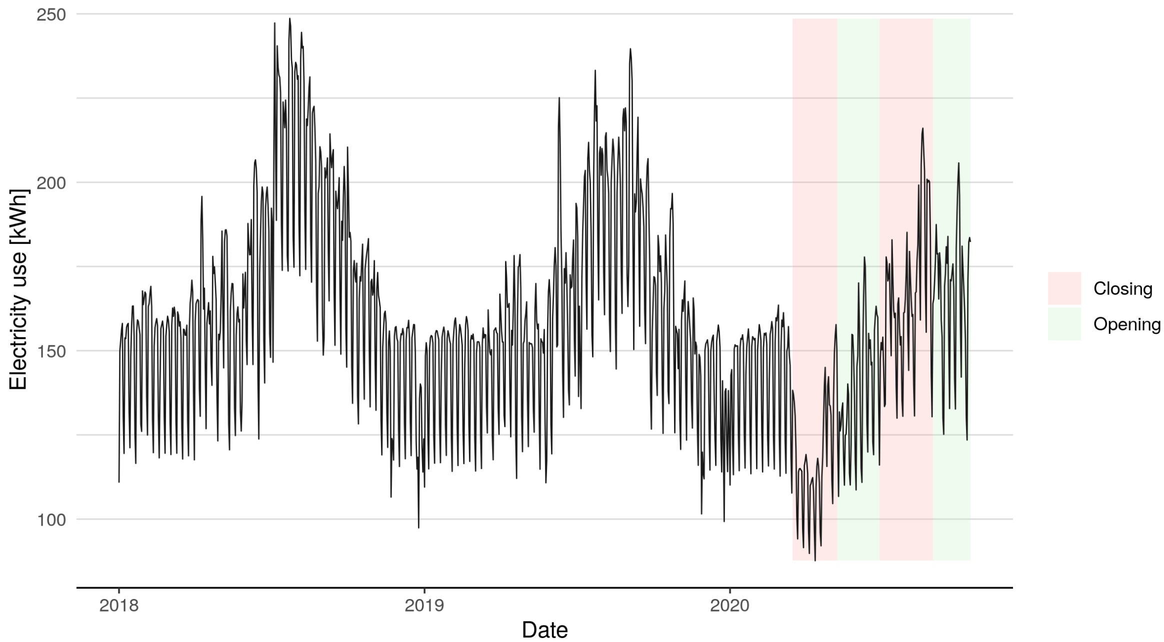
In this appendix, we perform two sets of robustness checks. First, we perform an outliers analysis, and second, we test an alternative business definition.

1.D.1. Outliers analysis

The following repeats the major elements of our business activity analysis, based on our original sample of 14 industries. However, the sample here is modified based on an outliers analysis where: (1) we identify businesses with electricity use in any hour in the top 1% across all business-hours; (2) for each of these businesses, we drop them entirely from the panel; and, (3) we rerun analyses based on the updated sample.

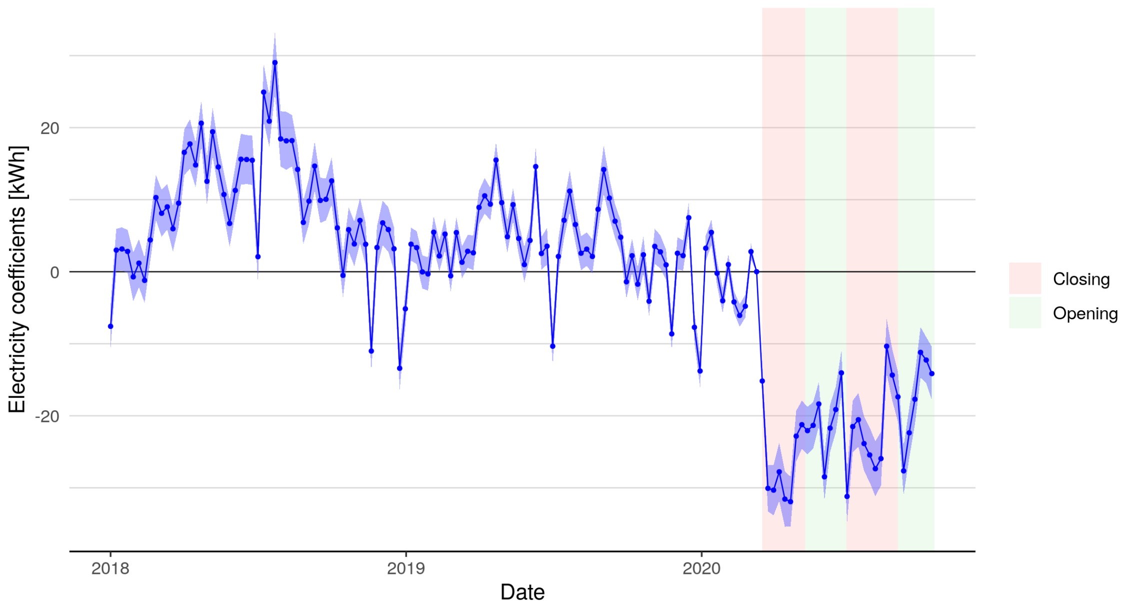
Given the plots and tables below, the results from the outliers analysis reduce magnitudes and variability. However, our main conclusions are stable to the procedure. Note that the activity results by loan do not show as much differentiation as in the text. This is likely a consequence of the original 'loan' and 'no loan' groups having limited overlap across their supports, and this difference subsequently narrowing through the outliers procedure. Yet, the line for those who receive a loan is still above the one for those who do not in Figure 1.D.4. A planned matching exercise will address many of the limitations of our analysis described in this paragraph.

Figure 1.D.1. Business daily average electricity use

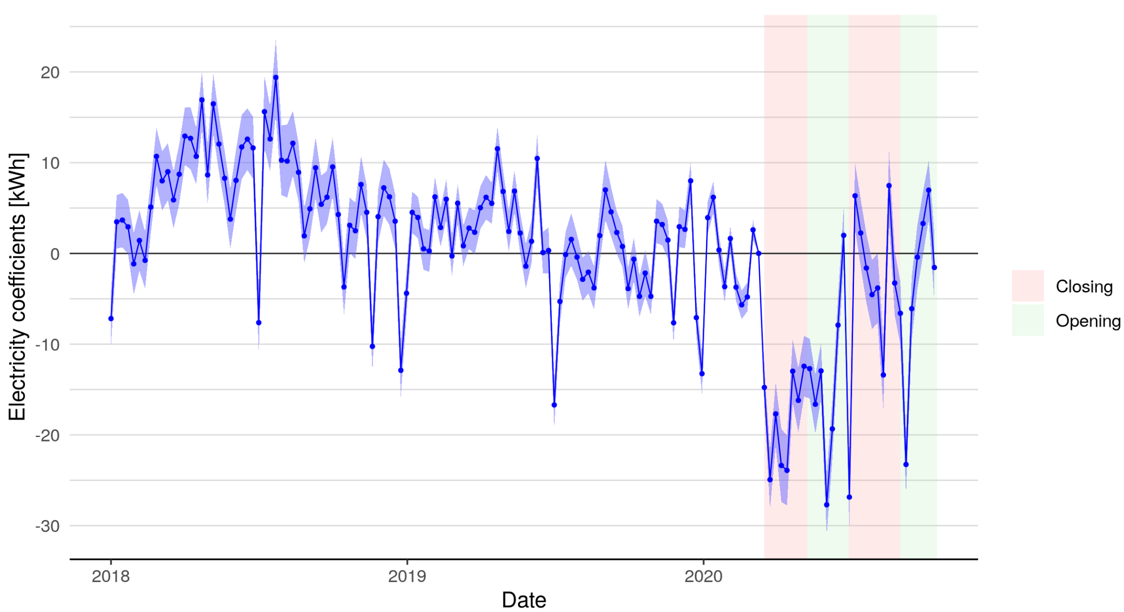


Notes: The full sample companion is Figure 1.3. The plot presents average daily electricity usage per business between 1 January 2018 and 15 October 2020. Businesses are defined as name-account-address tuples and restricted to the 14 industries identified in Section 1.4.2. Shaded areas represent closing and opening periods within LA County.

Figure 1.D.2. Residuals for daily electricity use per business



(a)



(b)

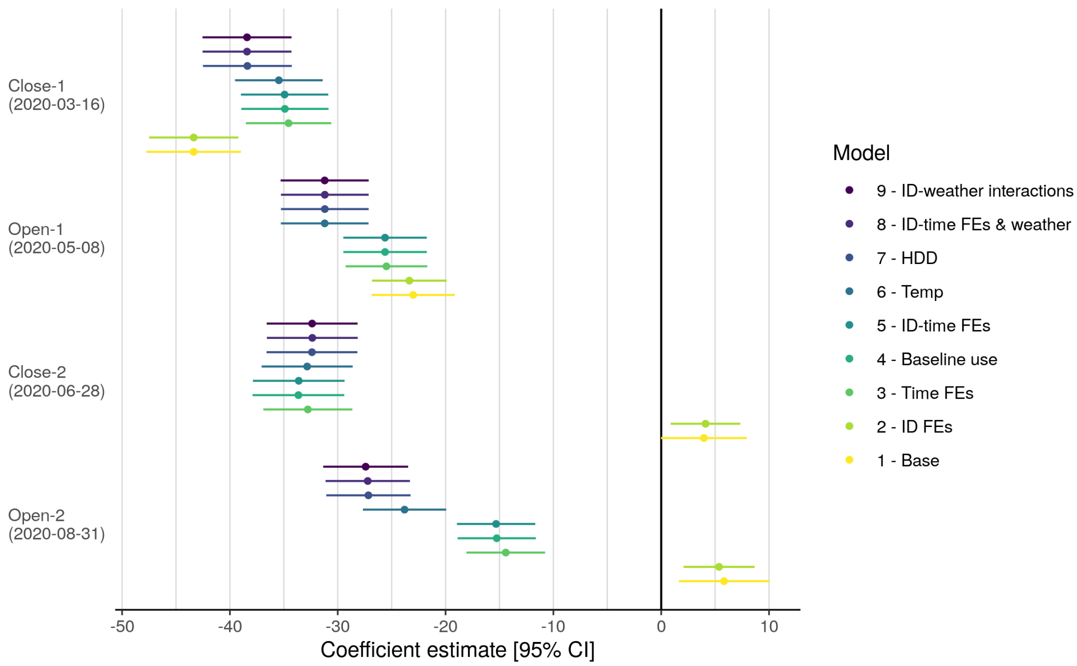
Notes: The full sample companion is Figure 1.8. The plots display residuals for daily electricity use per business averaged at the weekly level along with their 95% confidence intervals. Panel (a) is generated from a regression including weather and baseline use controls as well as business, day-of-week and month-of-year fixed effects. Panel (b) is generated from the same regression but with the addition of Burbank COVID case numbers. We use robust standard errors and cluster at the business level. The regression is estimated using data from Jan 2018 to Oct 2020 for all businesses within the 14 industries highlighted in the text. Red and green shaded areas represent closing and opening restriction periods within LA County.

Table 1.D.1. Panel event study regressions for daily electricity use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Close-1 (2020-03-16)	-43.37^{***}	-43.36^{***}	-34.56^{***}	-34.90^{***}	-34.93^{***}	-35.46^{***}	-38.38^{***}	-38.41^{***}	-38.41^{***}
	(-19.39)	(-20.56)	(-17.11)	(-16.91)	(-16.91)	(-17.08)	(-18.26)	(-18.27)	(-18.25)
Open-1 (2020-05-08)	-23.00^{***}	-23.36^{***}	-25.48^{***}	-25.61^{***}	-25.61^{***}	-31.21^{***}	-31.20^{***}	-31.20^{***}	-31.21^{***}
	(-11.71)	(-13.22)	(-13.19)	(-12.97)	(-12.97)	(-15.04)	(-15.04)	(-15.04)	(-14.98)
Close-2 (2020-06-28)	3.96	4.11^{*}	-32.77^{***}	-33.65^{***}	-33.62^{***}	-32.84^{***}	-32.39^{***}	-32.36^{***}	-32.37^{***}
	(1.95)	(2.49)	(-15.56)	(-15.52)	(-15.51)	(-15.24)	(-15.07)	(-15.06)	(-15.06)
Open-2 (2020-08-31)	5.83^{**}	5.36^{**}	-14.42^{***}	-15.25^{***}	-15.31^{***}	-23.80^{***}	-27.16^{***}	-27.22^{***}	-27.41^{***}
	(2.72)	(3.19)	(-7.74)	(-8.24)	(-8.27)	(-12.09)	(-13.62)	(-13.64)	(-13.64)
Temperature						1.71^{***}	0.78^{***}	0.78^{***}	
						(29.71)	(15.59)	(15.57)	
HDD							1.68^{***}	1.69^{***}	
							(26.08)	(26.09)	
ID FE		X	X	X	X	X	X	X	X
Day-of-Week FE			X	X		X	X		
Month-of-Year FE			X	X		X	X		
ID-Month Baseline				X	X	X	X	X	X
ID:Day-of-Week FE					X			X	X
ID:Month-of-Year FE					X			X	X
ID:Temp Int									X
ID:HDD Int									X
Businesses	4,738	4,738	4,738	4,473	4,471	4,473	4,473	4,471	4,471
Observations	4,329,435	4,329,435	4,329,435	4,255,560	4,255,541	4,255,560	4,255,560	4,255,541	4,255,541
R^2	0.001	0.904	0.908	0.926	0.952	0.926	0.927	0.953	0.956
Adjusted R^2	0.001	0.904	0.908	0.925	0.951	0.925	0.926	0.951	0.954

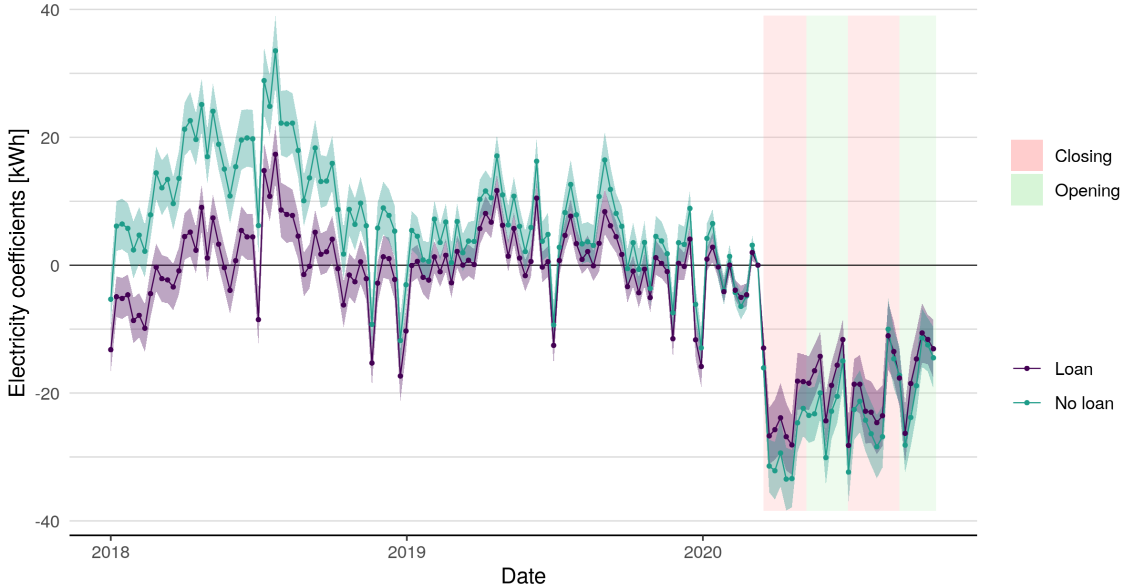
Notes: The full sample companion is Table 1.3. This table reports results from nine separate regressions. The dependent variable in all regressions is daily electricity use measured at the business level, where businesses are defined as name-account-address tuples. The main variables of interest are event-study period indicators signifying intervals with either tightening or relaxing COVID restrictions, respectively. We use robust standard errors and cluster at the business level. The regression is estimated using data from January 2018 to October 2020 for all businesses within the 14 industries highlighted in the text. Significance is represented as *** for $p<0.001$, ** for $p<0.01$, and * for $p<0.05$; while, t-statistics are in parentheses.

FIGURE 1.D.3. Restriction coefficients for daily electricity use per business



Notes: The full sample companion is Figure 1.9. The plot displays restriction coefficients for daily electricity use per business along with their 95% confidence intervals from Table 1.D.1. It is generated from a regression including weather and baseline use controls as well as business, day-of-week and month-of-year fixed effects. We use robust standard errors and cluster at the business level. The regression is estimated using data from January 2018 to October 2020 for all businesses within the 14 industries highlighted in the text.

FIGURE 1.D.4. Residuals for daily electricity use per business by loan receipt



Notes: The full sample companion is Figure 1.11. The plot displays residuals for daily electricity use per business averaged at the weekly level along with their 95% confidence intervals. The residuals are from two separate regressions with the first based on the sample of businesses receiving a federal loan, and the second not. The regressions include weather and baseline use controls as well as business, day-of-week and month-of-year fixed effects. We use robust standard errors and cluster at the business level. The regression is estimated using data from January 2018 to October 2020 for all businesses within the 14 industries highlighted in the text. Red and green shaded areas represent closing and opening restriction periods within LA County.

Table 1.D.2. Panel event study regressions for daily electricity use by loan receipt

	All Data		**No loan**		**Loan**	
	(1)	(2)	(3)	(4)	(5)	(6)
Close-1 (2020-03-16)	-34.56^{***}	-37.98^{***}	-38.66^{***}	-42.25^{***}	-24.07^{***}	-27.04^{***}
	(-17.11)	(-18.48)	(-14.69)	(-15.78)	(-9.67)	(-10.67)
Open-1 (2020-05-08)	-25.48^{***}	-30.97^{***}	-29.25^{***}	-35.26^{***}	-15.83^{***}	-19.90^{***}
	(-13.19)	(-15.28)	(-11.58)	(-13.31)	(-6.84)	(-8.23)
Close-2 (2020-06-28)	-32.77^{***}	-31.53^{***}	-35.90^{***}	-34.57^{***}	-24.56^{***}	-23.56^{***}
	(-15.56)	(-15.10)	(-13.10)	(-12.73)	(-9.49)	(-9.18)
Open-2 (2020-08-31)	-14.42^{***}	-26.07^{***}	-16.18^{***}	-28.78^{***}	-9.82^{***}	-18.99^{***}
	(-7.74)	(-13.09)	(-6.69)	(-11.13)	(-4.23)	(-7.69)
Temperature		0.76^{***}		0.88^{***}		0.44^{***}
		(15.48)		(13.87)		(7.29)
HDD		1.66^{***}		1.73^{***}		1.47^{***}
		(26.45)		(21.40)		(18.26)
ID FE	*X*	*X*	*X*	*X*	*X*	*X*
Day-of-Week FE	*X*	*X*	*X*	*X*	*X*	*X*
Month-of-Year FE	*X*	*X*	*X*	*X*	*X*	*X*
Businesses	4,738	4,738	3,513	3,513	1,225	1,225
Observations	4,329,435	4,329,435	3,149,361	3,149,361	1,180,074	1,180,074
R^2	0.91	0.91	0.91	0.91	0.90	0.90
Adjusted R^2	0.91	0.91	0.91	0.91	0.90	0.90

Notes: The full sample companion is Table 1.5. This table reports results from nine separate regressions. This table reports results from six separate regressions. The dependent variable in all regressions is daily electricity use measured at the business level, where businesses are defined as name-account-address tuples. The main variables of interest are event-study period indicators signifying intervals with either tightening or relaxing COVID restrictions, respectively. The sample for Columns (1) and (2) contains all businesses and replicate Columns (4) and (7) from Table 1.D.1. The sample for Columns (3) and (4) is limited to only those businesses not receiving a federal loan, while that for Columns (5) and (6) is limited to those that do. We use robust standard errors and cluster at the business level. The regression is estimated using data from Jan 2018 to Oct 2020 for all businesses within the 14 industries highlighted in the text. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, *t*-statistics are in parentheses.

1.D.2. Alternate business definition

We perform tests on an alternate business definition, namely: name-street pairs. We repeat the activity regressions for the alternative definition using names and streets as the basis of aggregation. The original results are presented in Section 1.5.2 and are similar to those presented here. They differ in that they are slightly less significant and of a larger negative magnitude due to additional aggregation inherent in the alternative definition. Nevertheless, the take-away message is that COVID restrictions led to a reduction in business activity, and the relaxation of these restrictions led to increased activity.

TABLE 1.D.3. Panel event study regressions for daily electricity use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Close-1 (2020-03-16)	−85.87***	−89.79***	−71.27***	−72.39***	−72.47***	−73.46***	−78.37***	−78.45***	−78.49***
	(−6.20)	(−6.19)	(−5.40)	(−5.34)	(−5.34)	(−5.38)	(−5.60)	(−5.60)	(−5.59)
Open-1 (2020-05-08)	−49.27***	−54.38***	−56.12***	−57.17***	−57.18***	−67.89***	−67.86***	−67.87***	−68.08***
	(−3.89)	(−4.07)	(−4.33)	(−4.29)	(−4.29)	(−4.85)	(−4.85)	(−4.85)	(−4.85)
Close-2 (2020-06-28)	11.20	2.25	−69.59***	−72.37***	−72.23***	−70.81***	−70.06***	−69.92***	−69.93***
	(0.45)	(0.19)	(−4.86)	(−4.84)	(−4.84)	(−4.77)	(−4.73)	(−4.73)	(−4.73)
Open-2 (2020-08-31)	36.04	13.32	−28.16*	−30.85*	−30.98*	−47.21***	−52.83***	−52.96***	−53.70***
	(1.00)	(1.07)	(−2.34)	(−2.50)	(−2.51)	(−3.80)	(−4.15)	(−4.15)	(−4.20)
Temperature						3.27***	1.71***	1.71***	
						(8.40)	(5.18)	(5.18)	
HDD							2.83***	2.83***	
							(8.40)	(8.40)	
ID FE		X	X	X	X	X	X	X	X
Day-of-Week FE			X	X		X	X		
Month-of-Year FE			X	X		X	X		
ID-Month Baseline				X	X	X	X	X	X
ID:Day-of-Week FE					X			X	X
ID:Month-of-Year FE					X			X	X
ID:Temp Int									X
ID:HDD Int									X
Businesses	4,270	4,270	4,270	4,083	4,082	4,083	4,083	4,082	4,082
Observations	3,980,550	3,980,550	3,980,550	3,922,870	3,922,854	3,922,870	3,922,870	3,922,854	3,922,854
R^2	0.000	0.962	0.962	0.971	0.981	0.971	0.971	0.981	0.983
Adjusted R^2	0.000	0.962	0.962	0.971	0.981	0.971	0.971	0.981	0.983

Notes: The full sample companion is Table 1.3. This table reports results from nine separate regressions. The dependent variable in all regressions is daily electricity use measured at the business level, where businesses are defined as name-street pairs. The main variables of interest are event-study period indicators signifying intervals with either tightening or relaxing COVID restrictions, respectively. We use robust standard errors and cluster at the business level. The regression is estimated using data from January 2018 to October 2020 for all businesses within the 14 industries highlighted in the text. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, *t*-statistics are in parentheses.

CHAPTER 2

Government ownership and market power: An investigation of the Stanwell Direction in Queensland, Australia

Co-Author:

James B. Bushnell

2.1. Introduction

The Great Recession has left a lasting impact on the world economy (e.g., Jenkins et al., 2012; Margerison-Zilko et al., 2016; Yagan, 2019), affecting, among others, the market structure in many industries. Since then, high market concentrations and record markups have been observed globally (De Loecker and Eeckhout, 2018; García-Perea, Lacuesta and Roldan-Blanco, 2021; Grullon, Larkin and Michaely, 2019; Linnemann, 2016). Associated economic ills include a decline in the labor share (Barkai, 2020), falling labor productivity (Autor et al., 2017, 2020), and a slowdown in aggregate output (De Loecker, Eeckhout and Unger, 2020).

Concurrently, the Great Recession rekindled interest in public firms. Government-owned companies constitute an important policy tool, though views on their merit have changed significantly over time. While much of the 20$^{\text{th}}$ century saw government dominate the commanding heights, through the 1980s, 1990s and well into the new millennium, the prevailing trend in Western countries saw governments divest from economic functions and expose previously public industries to the discipline of the market (Williamson, 2009). Known as the "Washington Consensus," its underlying principle was that private firms, through a singular focus on profit maximization, were more efficient than public ones (Megginson and Netter, 2001). The Great Recession forced many governments re-evaluate public ownership as a useful policy tool Bernier (2014); Florio (2013); Florio and Fecher (2011), none more spectacularly or successfully than the US and the bailouts under the TARP program (Megginson, 2017).

One reason why public ownership may be seen as particularly appealing is that through government-owned companies policymakers are capable of exerting direct political influence (Dinç, 2005). As highlighted by Sappington and Stiglitz (1987), government-ownership reduces intervention costs. Significant government-ownership in a given industry allows policymakers to exert direct influence over both market structure and conduct, among other elements. With concerns over market power and equity becoming more prominent, access to such a channel of influence could be more valuable than the ability to tighten regulatory controls or increasing antitrust oversight.

To better understand the intertwined effects of government ownership and market power, we study the Australian National Electricity Market (NEM), where significant generating assets remain government-owned. We do so primarily in the context of the "Stanwell Direction" made by the

Queensland (QLD) Government in June 2017. The Direction was a formal instruction by the state government to Stanwell Corporation, a government-owned generator, to alter its bidding strategies in order to put downward pressure on wholesale electricity prices (QLD Government, 2017*a*,*b*). In the months leading up to the Direction, the NEM had experienced a persistent rise in prices across the market (ACCC, 2018; AER, 2018*b*). The increases were attributed to various market trends and events, including: a tightening supply-demand balance, partly due to the recent closure of Hazelwood Power Station (HPS), a major coal-fired plant in Victoria (VIC); increasing black coal prices in QLD and New South Wales (NSW) and gas prices across the NEM; and, high levels of market concentration.

The Direction was an extraordinary step. In particular, since the formation of the NEM, the Commonwealth and state governments had not directly intervened in the day-to-day operations of electricity market participants. In addition to the Direction, the QLD Government also announced a set of other policies intended to ease wholesale prices, none of which were anticipated to have any effect in the short term.[1] Only the Direction was capable of affecting the market in the near term, and, in fact, it was credited with lowering prices almost immediately.[2] However, its effects on price-cost margins and market power within the NEM have never been empirically assessed.

We first review the history of government ownership within the QLD electricity sector. We focus on the Government's original reasoning for maintaining public ownership, how government decisions affected market structure and concentration, and how high levels of concentration could have precipitated specific market power strategies employed by government-owned generators. We then turn to an investigation of the effects of the Direction on the prevalence of market power. We base our analysis on a competitive benchmark model of the NEM that we build following Borenstein, Bushnell and Wolak (2002). Our model relies on various data, including high-resolution electricity market data from the Australian Energy Market Operator (AEMO), as well as fuel

[1] Other measures within the "Powering Queensland Plan" QLD Government (2017*b*) targeted towards reducing wholesale prices included: returning a mothballed gas-fired station to service; promising to reorganize government generation through the establishment of a government-owned renewable energy generator; and, facilitating additional renewable energy investment in the state. While likely to have substantial market impacts in the future, none of these policies were likely to influence prices the immediate aftermath of the Plan's announcement.

[2] As stated by the Premier (Palaszczuk, 2017): "In the 24 hours following our announcement last week, forward wholesale power prices fell by 10 per cent in Queensland and by four per cent in New South Wales. I never thought I would say it, but we are actually helping New South Wales."

prices and generator characteristics from other sources. Unlike many other industries, the study of electricity markets benefits from a known and simple cost structure and wide availability of cost data. As such, our model estimates counterfactual prices under the assumption of perfect competition.[3] Thus, when compared to actual market prices, it allows us to estimate price-cost margins and the Lerner index—two common measures of market power—for the generation sector.

The comparison of actual market outcomes with our competitive simulations suggests that abuses of market power by QLD generators during high-demand periods decreased after the release of the Direction. This likely accounts for the reduction in high price events and, subsequently, the average market price in QLD post-Direction. However, we find no evidence of the Direction affecting markups at lower levels of demand. In fact, our analysis indicates that generators continued to exercise market power and earn profits in excess of competitive rents in QLD during the post-Direction period. With respect to customer impacts, we find that the Direction's effects were symmetric for both QLD and NSW customers.

The remainder of the chapter is organized as follows. Section 2.2 provides an overview of the literature related to ownership and market power. Section 2.3 describes the NEM and its key institutional features, including its operation, structure and susceptibility to market power. Section 2.4 reviews the QLD Government's involvement in the generation sector as well as the history leading up to the Direction and its aftereffects. Section 2.5 introduces our competitive benchmark model, while Section 2.6 discusses the data and how various source materials were merged into a unified set. Section 2.7 presents our results and Section 2.8 concludes.

2.2. Literature Review

This chapter contributes to two strands of the existing literature: (1) the effects of ownership; and, (2) the measurement of market power. Within the former, our work most closely aligns with empirical studies investigating how ownership influences market prices and margins in competitive industries (e.g., Asaftei and Parmeter, 2010; Konings, Van Cayseele and Warzynski, 2005). Our work differs by analyzing margins at the market level, whereas, previously, studies focused

[3] Since the NEM is a zonal market, we simulate each settlement interval between 2015 and 2019 to produce counterfactual competitive timeseries for each region.

on firm-level effects. For the latter, we contribute to the long tradition of competitive benchmark models, which assess market power and strategic behavior in wholesale electricity markets (Borenstein, Bushnell and Wolak, 2002; Wolfram, 1999). We are the first to develop such a model for the Australian NEM.

2.2.1. Ownership

Ownership, which refers to rights over residual revenues (Vickers and Yarrow, 1991), can affect the optimization problems that facilities face and may thus be important for market outcomes in the electricity sector. The following discussion focuses on the choice between public and private ownership.[4] However, it should be noted that these represent the extremes of the continuum of governance structures reflecting the level of regulation over public- and privately-owned firms (Laffont and Tirole, 1993; Sappington and Stiglitz, 1987).

Private ownership typically leads managers to emphasize the pursuit of profits; whereas, the goals pursued under public ownership may be much broader. To illustrate how these differences translate into welfare outcomes, consider the simplified model developed by Shapiro and Willig (1990) and adapted in Vickers and Yarrow (1991). Suppose a firm is under public ownership. It is run by a public servant who maximizes social welfare and their own personal agenda. The latter could consist of a variety of elements, including: high wage and employment levels, redistribution to favored interest groups and regions, etc. More formally, let us assume that the public servant's objective U is a weighted average of social welfare W and their personal agenda P:

$$U(x) = W(x) + \mu P(x)$$

where x is a vector of decision variables and μ reflects the weight of the private agenda relative to social welfare. Under private ownership, suppose the firm is run to maximize profit. Profit π is a component of social welfare along with the byproduct effects caused by the firms' activities. These could include deadweight loss from the exercise of market power, positive or negative externalities,

[4] 'Public' ownership is synonymous with 'government' ownership herein.

etc. If welfare is again denoted by W and net externalities by E, we have:

$$\pi(x) = W(x) - E(x).$$

In each case, social welfare and the objectives of the decision makers diverge, such that all forms of ownership are potentially inefficient (Vickers and Yarrow, 1991). For private firms, "market failures" drive a wedge between private profit and social welfare objectives. Whereas, for public firms, "government failures" lead to a divergence between private political and social welfare objectives. Thus, the effects of ownership on welfare depend upon the relative magnitudes of these inefficiencies. Privatization can be viewed as a means of reducing the impact of government failure, albeit at the risk of potential market failures.

If the personal agenda, P, and net externalities, E, depend on other variables, such as market characteristics or political environment, the welfare superior ownership regime may vary across settings. Consequently, comparison between ownership regimes may need to be conducted separately for each case. To understand how such comparisons can be made, the first subsection of this paper surveys the theoretical literature contrasting market and government inefficiencies. The next subsection provides an overview of the empirical literature which attempts to establish the contexts where public versus private ownership is preferred in practice.

Theory

The theoretic literature on ownership utilizes first-best outcomes as its benchmark, where social welfare maximization requires both the production of the optimal mix of goods as well as the production of each good with the minimum amount of resources (Putniņš, 2015). The first requirement is referred to as allocative efficiency and is met by allocating goods to their most valuable uses. The second is referred to as technical efficiency and is met by producing goods at the lowest possible cost.

Note that Lawson (1994) and Cavaliere and Scabrosetti (2008) provide surveys on the theoretical underpinnings of public versus private companies

Market failure. If competitive markets left to their own devices allocate resources efficiently and utilize the lowest cost means of production, the role for a government guided by welfare maximization is negligible (Putniņš, 2015). Thus, the theoretical argument for private ownership of the means of production rests on the first fundamental theorem of welfare economics. When markets are complete, any competitive equilibrium is necessarily Pareto optimal (Mas-Colell, Whinston and Green, 1995, pp. 150-151). The corollary suggests that a breakdown of the ideal conditions argue for government intervention. And indeed, governments regularly act to correct market failures, such as owning or regulating natural monopolies, providing public goods, and intervening when externalities arise (Megginson and Netter, 2001).

For natural monopolies—such as, electricity and water supply—high fixed costs and/or powerful economies of scale make it uneconomic for more than one producer to operate, creating the potential for significant market power abuse. In these circumstances, government ownership is one potential solution to avoid overpricing and undersupply (Yarrow, 1986).[5] Public goods—such as, defense and air quality—are non-excludable and non-rivalrous. Profit-oriented, private actors are not incentivized to produce public goods, such that these goods are typically undersupplied or lack a market entirely.[6] Finally, despite typically being addressed through regulation or incentives, externalities can also be internalized through government ownership. Here, the assumption is that citizens suffering from negative externalities could punish their political representatives through elections.[7]

In each case above, the rationale for government intervention rests on an argument that markets have failed and government can step in to resolve the failure (Megginson and Netter, 2001; Yarrow, 1986). That is, government intervention may be desirable when markets alone are unable to realize Pareto-efficient outcomes (Radić, Ravasi and Munir, 2021). Government ownership constitutes one possible intervention, and therefore, the presence of these failures indicate markets where there may exist an economic rationale for operating government-owned companies (Putniņš, 2015).

[5] An alternative solution is the creation of a regulatory regime, which avoids direct government participation in service delivery. Though, it increases informational asymmetries between management and those responsible for monitoring their performance.

[6] When markets fail to form, they are called 'missing markets,' where public goods are considered a special case in that demand exists, but supply is absent.

[7] Alternatively, citizens benefiting from positive externalities could instead reward their political representatives.

Government failure. Similar to the way various imperfections prevent markets from realizing Pareto efficiency, government interventions can also fail to maximize social welfare. Collectively, the reasons for inferior welfare outcomes under government intervention are known as government failures (Le Grand, 1991).

The overarching argument against government ownership is based on the technical inefficiency of government production,[8] which is underpinned by the microeconomic theories of property rights (Hart and Moore, 1990) and agency (Jensen and Meckling, 1976).[9] This can be summarized as a misalignment of incentives between the government, its firms and the public at large. The important implication of technical inefficiency in government-owned companies is that: given resource inputs, less than the full potential output is produced; or alternatively, given outputs, more than the minimum amount of input resources are used (Putniņš, 2015). Drivers of technical inefficiencies include diffuse property rights, multiple objectives, soft budget constraints and the crowding-out of investment. While each of theses issues are not necessarily exclusive to public firms, theory suggests that they are more likely to suffer from them as compared to private firms.

Property rights theory is related to the effects of ownership on resource usage. One of its fundamental principles is that owners are incentivized to efficiently manage their assets (Hart and Moore, 1990). Public ownership, however, 'dilutes' property rights and reduces the incentive to manage assets efficiently. Political representation can be highly imperfect, weakening the incentives for efficient monitoring of both public enterprises and government stewardship. Most voters lack specialist knowledge about actual and potential performance of nationalized industries. When coupled with an inability to vote separately on this issue, the performance of government-owned companies tends to have only a minor effect on electoral outcomes (Yarrow, 1986). In addition, it is difficult to write complete contracts that link management incentives to a profit maximization objective (Shleifer, 1998). In contrast, private ownership curtails many of these weaknesses. Private owners have the 'undiluted' property rights. As such, they are more likely to have specialist knowledge of the particular industry, and they can monitor and contract performance more easily when management objectives are reduced to profit maximization.

[8] In addition to technical inefficiency, the welfare implications of government-owned companies should also consider opportunity costs—i.e. the alternative uses of the capital committed to government production.

[9] Note that 'technical inefficiency' incorporates the 'political agenda' from the model introduced at the beginning of this section.

Agency theory complements the above in that it relates to the potential for divergent objectives between ownership and management (Jensen and Meckling, 1976). It highlights the mechanisms through which principals incentivize agents to act according to shareholder interests (Fama and Jensen, 1983). The application of agency theory to the analysis of government ownership foreshadows certain principal-agent problems (Megginson and Netter, 2001). First, government ownership can complicate firm objectives. Since governments have multiple goals—including social welfare, political interests, profitability, etc.—a public shareholder is unlikely to solely prioritize operational efficiency. Instead, managers can be expected to split their attention between a broader set of goals (Vickers and Yarrow, 1991).[10] Further complicating matters, these objectives frequently change from one administration to the next. The inability of government to credibly commit to a fixed policy can, thus, adversely impact technical efficiency. Private ownership, on the other hand, encourages managers to focus on a single, well-defined corporate goal: long-term profit maximization (Megginson and Netter, 2001).

Second, governments are thought to have weak incentives to properly monitor economic performance (Vickers and Yarrow, 1991). Government-owned companies are assumed to have 'soft' budget constraints diminishing the drive for efficiency. The discipline of capital markets is less important for publicly-owned firms, as losses may be systematically covered by the government (Megginson and Netter, 2001). If government-owned companies can survive without recourse to costs, such mechanisms may no longer guide behavior and encourage waste. Private ownership places managers under stricter control, since private investors have a stronger incentive to closely monitor decisions that directly affect their wealth.

In competitive markets, the absence of such cost stringency could have wider industry implications. Soft budget constraints—caused by implicitly subsidized capital such as debt guarantees or equity injections at below market rates—provide an unfair advantage to government-owned companies (Putniņš, 2015). Governments may also bestow subsidies and grants, favorable regulation, and preferential access to government contracts (Bortolotti, Cambini and Rondi, 2013). Even

[10] Note that the market failure rationale implies government-owned companies will necessarily respond to nonfinancial objectives (Putniņš, 2015). If a government firm is restricted to only a profit-maximizing objective, it is reasonable to expect that a transfer to private ownership and operation will maximize social welfare. Therefore, the performance of government-owned companies cannot be evaluated using only financial indicators as is common in the private-sector.

when government-owned companies operate at a lower level of technical efficiency, such support can crowd-out desirable private-sector investment and entry (Atukeren, 2005). This could have harmful allocative efficiency effects, if the lack of investment results in higher market concentration and increased potential for market power in the long-run.

Arguments beyond efficiency considerations. Sociopolitical arguments for government ownership are based on companies pursuing non-commercial objectives beyond traditional economic efficiency (Christiansen, 2013; Shapiro and Willig, 1990). The use of government-owned companies is sometimes advocated as a means to deliver socially-desirable outcomes—including but not limited to regional development, job creation, and redistribution of income—that purely profit-oriented, private firms would not make in the absence of regulation or incentives (Shirley, 1999; Shirley and Walsh, 2000).

Many of the catalogued reasons for government intervention, even if not framed as market failures, are in fact underpinned by some form of market inefficiency (Putniņš, 2015). That is, where the motivation for a government-owned company is not explicitly a response to market failures, its rationale can be frequently framed as one. For example, employment can be viewed as a public good as it promotes social cohesion and general well-being, neither of which are excludable nor rivalrous. Unemployment, on the other hand, is correlated with negative externalities such as increased crime, poverty and unhappiness (e.g. Dooley, Fielding and Levi, 1996; Öster and Agell, 2007; Saunders, 2002). As these socially-desirable effects can be framed as market failures, even though at first sight they may seem detached from efficiency considerations, makes clear that government-owned companies are one possible policy prescription for addressing unemployment (Cavaliere and Scabrosetti, 2008).

Summary. Theoretical results are ambivalent regarding the impact of ownership on technical efficiency (Cavaliere and Scabrosetti, 2008). Government intervention is not a panacea for market failure, since government-owned companies are likely to involve some degree of technical and allocative inefficiency (Putniņš, 2015). However, this should not lead to them being automatically dismissed as a policy prescription. Rather, any evaluation of ownership must include a comprehensive welfare evaluation. Operating a government-owned company is only justified when the welfare loss of the market failure exceeds the costs of government failure (Sappington and Stiglitz, 1987). In such circumstances, government-owned companies are best suited when: there already exists a competitive market (Yarrow, 1986); and, intervention goals are well defined with an emphasis on profit maximization (Putniņš, 2015). For the former criterion, the efficiency of public versus private ownership depends heavily upon both the degree of competition in the market as well as the regulatory environment (Shirley and Walsh, 2000).

Empirics

Dovetailing with the theory outlined above, there exists an extensive literature on ownership effects. In what follows, we limit our review to the effect of ownership on efficiency and prices. Nevertheless, the broader literature covers many other effects. [11] The literatures also investigates a wide diversity of industries [12] and ownership structures. [13]

Efficiency. The effect of public versus private ownership on technical efficiency has been extensively studied.[14] There are many surveys providing a comprehensive overview of the field, see for example: Frydman et al. (1999), Megginson and Netter (2001), Goldeng, Grünfeld and Benito (2008), Megginson (2017), Estrin and Pelletier (2018), and Radić, Ravasi and Munir (2021). Abbott and Cohen (2014) survey the literature with respect to Australian competition policy which

[11] Other ownership effects include but are not limited to: corporate social responsibility (Dam and Scholtens, 2012), employment (Dewenter and Malatesta, 2001; La Porta and López-de Silanes, 1999), environmental policies (Teodoro, Zhang and Switzer, 2020), factor prices (Ohlsson, 1996), internationalization (Radić, Ravasi and Munir, 2021), investment (Biggar and Söderberg, 2020; Di Pillo, Levialdi and Marchegiani, 2020), productivity (Brown, Earle and Telegdy, 2006, 2016), research and development (Kim, Kim and Flacher, 2012; Wang and Mogi, 2017), risk (Mohsni and Otchere, 2014), and quality (Petersen, Hjelmar and Vrangbæk, 2017).

[12] The sampling of the industries explored include: banks (Cornett et al., 2010; Megginson, 2005), electricity (Newbery and Pollitt, 1997), exploration (Karpoff, 2001), health care (Tynkkynen and Vrangbæk, 2018), heating (Egüez, 2021), manufacturing (Ramaswamy, 2001), oil (Wolf, 2009), parks (Lindholst, 2017), transport (Ehrlich et al., 1994; Oum, Adler and Yu, 2006; Pollitt and Smith, 2002; Scheffler, Hartwig and Malina, 2013), water (Walter et al., 2009), and waste (Bel, Fageda and Warner, 2010).

[13] Megginson (2017) provides a survey of the empirical literature for the effects of ownership across a variety of privatization structures, including: corporatization, contracting and outsourcing, initial public offerings, and sales or divestitures.

[14] The measurement of allocative efficiency is challenging due to data requirements and an emphasis on structural models. As a result, we are unaware of any existing studies investigating the effect of ownership on allocative efficiency.

commenced in the early 1990s.[15] The prevailing view is that government-owned companies are associated with lower technical efficiency.

Many papers, however, also emphasize that market structure and, in particular, competition are essential determinants of efficiency (Boardman and Vining, 1989). The argument here highlights that changes in government ownership—including privatization and corporatization—do not typically occur in a vacuum. Frequently, ownership changes are accompanied by broader market and regulatory reforms. This was the case during the Thatcher era in the UK, where the privatization of British Telecom was mirrored by the establishment of the telecommunications regulator Oftel (Yarrow, 1986). In Australia, the creation of the NEM coincided with both the establishment of oversight agencies—including the AER and AEMC—and the privatization of much of the electricity supply chain (Parer, 2002). Once the market structure is accounted for, studies frequently find that it is the dominant determinant of efficiency (e.g. Allen and Gale, 2000; Vickers and Yarrow, 1991). Nevertheless, Vining and Boardman (1992) note that ownership remains an important factor independent of the market structure. And still others suggest that private ownership is necessary for significant efficiency improvements (e.g. Boycko, Shleifer and Vishny, 1996; Shleifer, 1998).

Yarrow (1986) splits the difference by asserting that any evaluation of public versus private ownership must also consider the concurrent market structure and regulatory policies. Private ownership is known to be efficient in competitive conditions, but not necessarily so in the presence of market power. Vickers and Yarrow (1991) suggest that even under competitive market conditions, government ownership is not inherently less efficient than private ownership. If government-owned companies are not unfairly supported, public versus private ownership is likely to be similarly efficient under competitive conditions. Kole and Mulherin (1997) support these points through their investigation of how nationalization affects efficiency, all else equal. The authors sample a number of US firms with significant German or Japanese ownership prior to WWII. After the Attack on Pearl Harbor and America's entry into the War, the US government seized the common stock of these firms. Effectively, the government nationalized these firms up until their eventual sale long after the end of the War. The authors find no significant difference between the performance of

[15] With respect to Australia, Abbott (2006), Aghdam (2011), and Topp and Kulys (2012) evaluate the effect of deregulation on the efficiency of electricity supply. They find that competition likely increased efficiency, but are unable to find a causal link between privatization and increased efficiency. Nepal and Foster (2015) compare the efficiency of public versus private Australian electricity distribution companies.

their sample with private firms in the same industry. As these firms were operating in competitive industries prior to the forced takeovers, it forced the government to operate them efficiently. The results suggest that in a competitive environment, where the government represents a passive, profit-maximizing investor, factors other than ownership determine firm efficiency.

Generally, research supporting the conclusion that private firms are more efficient is linked to industries with pre-existing competitive markets (Megginson and Netter, 2001). This is true for banking (e.g. Bonin, Hasan and Wachtel, 2005), manufacturing (e.g. Xia and Walker, 2015), airlines (e.g. Al-Jazzaf, 1999), and pharmaceutical companies (e.g. Xu, Tihanyi and Hitt, 2017).

In markets with monopoly elements, Vickers and Yarrow (1991) argue that the critical factor is regulatory policy. In such industries, the effect of ownership on efficiency is ambiguous: some empirical studies give the advantage to public ownership, others to private ownership, and yet others find no significant difference between the two. These include research into electricity (e.g. Abbott, 2006), water (e.g. Walter et al., 2009), and telecommunications (e.g. Gasmi et al., 2013). Inconsistent results are most likely a consequence of the variations in regulatory regime and, consequently, the ability of the regulated monopoly to extract rents from the market.

These observations suggest that competitive markets encourage technical efficiency independent of public versus private ownership. Conversely, in noncompetitive markets—including both oligopoly and monopoly—market discipline is lacking. In the absence of regulatory conditions as a substitute for competition, private ownership is unlikely to foster efficiency gains and may even lead to a market failure.

Prices. The effect of government versus private ownership on output prices is less prominent in the literature. Nevertheless, this research question has been of interest since at least the early 1970s, see for example Peltzman (1971) and Meyer (1975).

Evidence from sectors prone to natural monopoly—such as electricity (Fiorio and Florio, 2013; Steiner, 2000), water (Chong et al., 2006; Martínez-Espiñeira, García-Valiñas and González-Gómez, 2009), telecommunications (Martin and Vansteenkiste, 2001), and district heating (Åberga, Fälting and Forssell, 2016; Egüez, 2021)—mostly support the hypothesis that private suppliers set higher prices than public ones. This is plausible given the nature of these industries, specifically their lack of competitive pressure and regulatory enforcement as a poor substitute. Some studies, however, do find that private monopoly suppliers set lower prices (Hattori and Tsutsui, 2004) or that ownership does not effect prices at all (Gassner, Popov and Pushak, 2009; Romano, Masserini and Guerrini, 2015; Zhang, Parker and Kirkpatrick, 2008). Such results are typically ascribed to unique country and/or industry features—including both institutions and norms. For example, Nikogosian and Veith (2012) interpret their null result as retailers prioritizing market share through lower prices, such that the threat of entry restricts the use of market power.

Early papers lacked robust samples and, so, relied on descriptive statistics techniques, such as difference-in-means, to compare price outcomes across ownership structure (Percebois and Wright, 2001; Saal and Parker, 2001). Later papers adopted either OLS or GMM regressions of prices on ownership and controls. Samples would consist of either cross-sectional (Nikogosian and Veith, 2012) or panel (Linden and Peltola-Ojala, 2010) data. More recently, given the potential endogeneity of ownership structure, papers moved to IV (Ruester and Zschille, 2010) or Heckman selection models (García-Valiñas, González-Gómez and Picazo-Tadeo, 2013; Porcher, 2017). In this sense, ownership choice is not orthogonal to the controls, but dependent on them. This accounts for the possible presence of sample selection bias.

For competitive industries, there have only been a handful of papers. Eckel, Eckel and Singal (1997) and La Porta and López-de Silanes (1999) both use descriptive statistics to estimate the effects of ownership on output prices. Eckel, Eckel and Singal analyze how the privatization of British Airways impacted airfares along contested routes. The authors compute a difference-in-means across periods controlling for industry price trends.[16] Average airfares in markets served by British Airways fell significantly upon privatization. The results suggest that a change from government to private ownership improved economic efficiency. La Porta and López-de Silanes compare how ownership affects output prices using a panel of firms from Mexico. They compute a difference-in-means across industries and periods. Price increases are found to be smaller in more competitive industries. Interestingly, the authors estimate that only a fraction of the increase in income-to-sales ratio is explained by higher prices and conclude that market power is not driving price increases.

[16] The control is defined as a passenger weighted average of price changes along routes of similar length where British Airways did not operate.

The next two papers, Konings, Van Cayseele and Warzynski (2005) and Asaftei and Parmeter (2010), formalize the estimation of the effect of ownership on price-cost margins. Following the technique developed by Hall (1988) and Roeger (1995), the authors utilize a semi-structural model derived from a Cobb-Douglas production function to estimate average markups. Both papers perform OLS regressions using a panel of manufacturing firms from Eastern Europe during its transition period shortly after the fall of the Soviet Union. They find smaller price-cost margins in competitive markets, while privatization is associated with higher markups. That is, private firms charge significantly higher markups on average than government-owned ones.[17]

Unfortunately, their approach is unable to separately estimate the effects of ownership on prices and costs. So it is not immediately clear whether higher price–cost margins are driven by lower costs—i.e. increased technical efficiency—or higher prices—i.e. the exercise of market power. That said, Asaftei and Parmeter note that the effect is stronger in competitive sectors, suggesting that firms reduce costs rather than increase prices since pricetaking behavior is synonymous with competitive markets. Furthermore, it suggests privatization without a competitive market environment may increase the potential for market power.

Literature investigating ownership effects on prices and price-cost margins are less prevalent than studies on efficiency effects for a number of reasons. First and foremost, the relationship between prices and ownership structure suffer from selection bias. As such, any identification strategy must address this endogeneity through an appropriate empirical methodology and the often commercial-in-confidence data necessary to implement it. For the latter, cost data are typically unobservable—either directly or indirectly through estimation procedures. These create high barriers for an empirical study and make it challenging, if not impossible, to interpret results causally with respect to the underlying drivers of price changes. Additionally, many industries, especially those with characteristics of a natural monopoly, have regulated prices. In such cases, the evaluation of price effects is not informative, so an analysis of technical efficiency is the preferred approach. Even if these hurdles are surmounted and an estimate is produced, it may still suffer

[17] Increased price-cost margins are not universally bad. For example, in cases where private firms charge higher prices, if abnormal profits are used to develop new technologies, welfare may improve if innovation leads to positive spillover effects. In other cases, price above cost may be desired in order for firms to cover their fixed expenditures, as is necessary in high-capital, increasing returns to scale industries, like electricity and water.

from bias resulting from systematic differences in output diversity and/or quality between publicly- and privately-owned firms.

The papers reviewed above strive to overcome these challenges, or at the very least persuade the reader that they are immaterial to their conclusions. Nevertheless, some concerns remain as each paper relies on accounting data, which can be susceptible to manipulation and measurement error. The papers using differences-in-means are potentially subject to omitted variables bias. Additionally, the markup results from papers like La Porta and López-de Silanes are indirect and only provide an illustrative estimate of the potential for market power. Finally, the papers utilizing the model developed by Hall and Roeger rely on a number of additional assumptions, which are not necessarily compatible with the study contexts. Due to insufficient degrees of freedom, the model restricts markups to be homogeneous. Moreover, the model requires that production technologies are constant returns to scale and that producers maximize profits. These are debatable given that the sample period includes transitioning from a command and control economy. In particular, the application of the return-to-scale constraint may result in an upward or downward bias in the markups.

2.2.2. Market Power

Electricity markets feature prominently in the literature on market power. In part, this reflects the industry's specific advantages as a subject for economic study.[18] Moreover, restructured electricity markets are particularly susceptible to the exercise of market power. This is attributable to inelastic supply and demand as well as a lack of large-scale, cost-competitive storage options (Borenstein, 2000). For the former, electricity demand is inelastic in the short run, because customers have limited or no incentive to modify behavior in accordance with hourly spot prices. Supply, on the other hand, becomes very inelastic as production approaches system capacity. For the latter, electrical energy must be consumed when it is generated due to the laws of physics. Current storage options are limited by a lack of available capacity, e.g. pumped hydro, or are still relatively

[18] As noted by Borenstein (2016) and Woerman (2021), these include: product homogeneity, which eliminates the challenges of product differentiation; perfectly inelastic and observed demand, obviating the need for its estimation; known production functions and the availability of cost data; and, a known market mechanism common to all participants.

expensive compared with the main generation technologies, e.g. batteries. Thus, even participants with a small market share can, at times of generation scarcity, raise wholesale electricity prices.[19]

A number of influential studies measure the exercise of market power in wholesale electricity markets (e.g., Borenstein, Bushnell and Wolak, 2002; Puller, 2007; Wolfram, 1999).[20] Moreover, the degree of market power has been found to depend on vertical integration (Bushnell, Mansur and Saravia, 2008), market organization (Mansur and White, 2012), the form of bidding (Reguant, 2014), arbitrage across market segments (Ito and Reguant, 2016), transmission infrastructure (Ryan, 2021), generation portfolio (Butner, 2020), and market structure (McDermott, 2020; Woerman, 2021). While these studies differ in methods, they can be broadly categorized according to whether they perform their measurement at the market or the unit level (Bushnell, Mansur and Novan, 2017).

Many of the studies belonging to this strand of literature are "market-level" studies, examining whether the market as a whole sets competitive prices given the production capabilities of all participants. They frequently rely on benchmarking models, where actual market outcomes are compared to various structural conduct paradigms. In the case of perfect competition, the benchmark is usually the marginal cost curve, equivalent to the merit order stack. It is built as a step function where units are ordered from lowest to highest marginal cost and combined with their expected capacities. This can thus easily serve as the basis for calculating the Lerner index.

Wolfram (1999) first applied these techniques to examining competition in restructured electricity markets. She finds statistically significant but modest market power within the England and Wales electricity market. Borenstein, Bushnell and Wolak (2002) apply these techniques to the California electricity crisis. They extend the competitive benchmark model to account for imports and hydro generation. Moreover, instead of derating capacity based on an expectation of

[19] In electricity markets, the most common forms of market power are economic and physical withholding—that is, respectively, by offering marginal generation at high prices or simply withholding capacity.

[20] This encompasses a small literature focusing on market power within the Australian NEM. Studies typically investigate a specific event. Dungey, Ghahremanlou and Long (2018) and Clements, Hurn and Li (2016) review rebidding behavior in QLD through a theoretic model and a descriptive analysis, respectively. Mountain and Percy (2019) performs a descriptive analysis of firm behavior before and after the closure of Hazelwood Power Station in VIC. Hu, Grozev and Batten (2005) perform a descriptive analysis of bidding behavior more broadly, while Marshall, Bruce and MacGill (2021) analyzes market power using concentration metrics.

forced outages, the authors use a Monte Carlo analysis of unit outages to estimate the distribution of available capacity. While their decomposition of wholesale electricity revenues assigns some responsibility to rising production costs and competitive rents, they find that the majority of the crisis could be attributed to the exercise of market power and generators bidding above marginal cost. Joskow and Kahn (2002) also investigate the California electricity crises. They use different data sources to recreate market-wide impact estimates, yet largely confirm the conclusions from Borenstein, Bushnell and Wolak (2002).

The above papers adopt a number of simplifying assumptions for the complexities of dispatch, as they are designed to be conservative by estimating the lower bound on the magnitude of market power. However, they have been criticized for adopting unrealistic system-wide production costs. Harvey and Hogan (2001) argue that competitive benchmark models should account for technological constraints; otherwise, market power estimates will be biased upwards. These constraints are defined as "dynamic" operation costs, such as minimum operating and minimum down times, ramping constraints, and unit startup costs. Mansur (2008) explores this issue in an analysis of markups in PJM, a regional transmission organization that operates in the Eastern US. He uses production and cost data from the year prior to PJM restructuring, when firms operated as regulated utilities, to estimate a reduced form model of generation costs. These estimates implicitly account for technological constraints that are ignored by "static" competitive benchmark models. He demonstrates that estimates of welfare can be significantly affected. Recently, Reynolds (2018) and Jha and Leslie (2021) have developed "dynamic" competitive benchmark models for the Texas and Western Australian electricity markets, respectively. They both find that "static" markup calculations overstate market power.

"Unit level" papers, on the other hand, investigate firm or generator supply decisions in order to assess individual behavior inconsistent with perfect competition. While the approach generally cannot provide market-wide estimates, it can instead identify the specific causes of market outcomes. Unit-level market power measurement techniques are heavily dependent on data availability, and include: capacity comparisons, bid benchmarking, residual demand analysis, and reduced-form regressions.

Papers testing individual-level behavior include Joskow and Kahn (2002) who study unit-level availability during the California electricity crisis. They compare unit generation to rated capacity during dispatch intervals when prices were significantly above estimated marginal costs. For a group of non-utility generators, they find a persistent disparity between their output and capacity during high-price periods.

Alternative tests of firm-level behavior examine offer bids and assess how they vary with market conditions. Wolfram (1998) implements a test of firm-level bidding in the England and Wales market. She finds that markups depend on the location within a firm's marginal supply curve, where the discrepancy between offer price and marginal cost increases at higher levels of dispatched generation. Hortaçsu and Puller (2008) use detailed firm-level data on bids and marginal costs from Texas to compare actual bidding behavior to static benchmarks. Large firms performed close to the theoretical benchmark of profit maximization. Smaller firms, however, utilized bid schedules which significantly deviated from this benchmark, which the authors suggest indicates a less sophisticated bidding strategy. Mercadal (2021) extends Hortaçsu and Puller's model to the case of sequential markets. Reguant (2014) combines bid-level data along with unit startups to estimate firm-level dynamic cost functions and market power in the Spanish electricity market. These are then used for counterfactual simulations of an individual firm's cost minimization problem. When comparing dynamic versus static competitive benchmarks, she also finds that the latter overestimates markups during peak periods.

A single firm's ability to raise prices will be a function of the aggregate market demand less the supply offers of these other firms. Thus, residual demand analysis can be used to assess the degree of market power possessed by a market participant. Wolak (2003), using bid data from California during the electricity crisis, estimates the residual demand faced by individual firms near the market clearing price. He finds that large firms possessed market power and their behavior was consistent with strategic profit maximization. Puller (2007) also studies the California crisis and formally tests the behavior of firms by examining alternative hypotheses of imperfect competition. He constructs an estimate of the residual demand elasticity faced by likely oligopolists. Using this estimate, he rejects tacit collusion and does not reject strategic profit maximization.

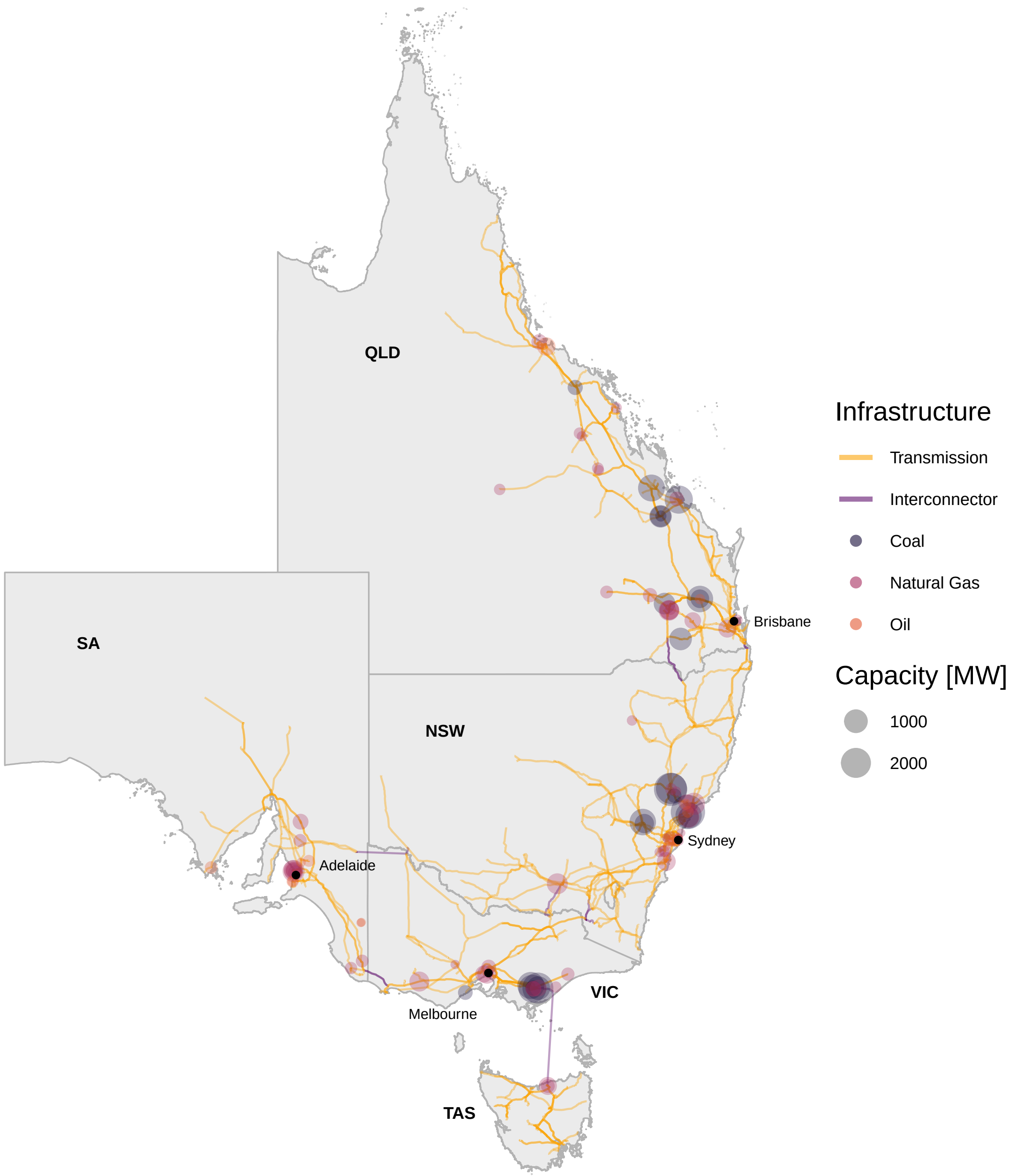
More recently, firm-level studies have attempted to measure market power using reduced-form techniques in lieu of the structural ones that predominated earlier. Davis and Hausman (2016) use plant-level data from California to document noncompetitive behavior following the shutdown of a major nuclear facility. They use "unit-level generation regressions" to tease out how plants respond to system-wide generation, which they then use to evaluate economic withholding at some units. McDermott (2020) and Woerman (2021) study the Norwegian and Texas electricity markets, respectively. Both papers exploit exogenous variation in market size and structure—arising from transmission constraints—to identify its causal impact on noncompetitive behavior. They find that the formation of localized electricity markets significantly increases markups. Finally, Butner (2020) uses reduced-form methods to investigate the behavior of integrated participants within MISO, a regional transmission organization that operates in the mid-Western US. He finds that market participants with greater wind capacity withhold their fossil-fired capacity more in response to increased wind generation.

2.3. National Electricity Market Background

The NEM is a self-contained electricity market on the eastern seaboard of Australia. It has been in existence since December 1998 and is operated by the Australian Energy Market Operator (AEMO). It is self-contained in that all load must be satisfied by generation from within the network. Figure 2.1 displays the topology of the NEM, including all fossil-fired generation and transmission infrastructure. The network consists of five regions, namely: New South Wales (NSW), Queensland (QLD), South Australia (SA), Tasmania (TAS) and Victoria (VIC). These regions are linked radially with VIC as the hub through six interconnectors: QNI and Terranora between NSW and QLD; the eponymous VIC-NSW; Heywood and MurrayLink between SA and VIC; and, BassLink between VIC and TAS.

The remainder of this section describes key elements of the NEM in further detail. In particular, it highlights its operation, structure and potential for market power.

Figure 2.1. NEM fossil-fired generation and transmission network



Notes: The map illustrates the geographic location all fossil-fired generation and transmission infrastructure within the NEM. The generation type is coded by color, while size is proportional to plant capacity. Regional interconnectors are identified by purple lines. Only infrastructure operating between 2015 and 2019 are displayed, along with all state capitals.

2.3.1. Market operation

The NEM is an energy-only, zonal, real-time electricity market. The 'energy-only' framework means generators are only paid for the electricity they produce. This is in contrast to markets which include some form of capacity payments – i.e., payments for simply being available to produce.

The NEM is a zonal market meaning that supply and demand are balanced within each region. Zonal pricing, and its counterpart nodal pricing, relate to congestion management. The former aggregates nodes into contiguous areas where uniform prices apply. A zone typically has low intra-grid congestion; hence, price differentials between zones reflect inter-grid congestion. With nodal pricing, transmission constraints are explicitly observed within the optimal system-wide dispatch permitting the calculation of locational marginal prices. Each generator is, thus, paid according to the local price at the node where it is connected to the transmission network.

Liberalized electricity networks contain a 'real-time' market, commonly called a spot market. Usually, it serves as the final precision balancing mechanism, where generation commitments are procured or relieved based on realized conditions in the market. This is typically proceeded by a series of advance bidding opportunities, where generation commitments are made in advance of the real-time market. These are commonly known as 'day-ahead' or 'hour-ahead' markets. Where the NEM differs is that it does not contain sequential markets leading up to dispatch: it is real-time only. Thus, all trading and scheduling is finalized within its spot market.

As the market operator, AEMO performs a number of important functions within the NEM. First, as the institution responsible for the NEM's real-time operation, AEMO ensures aggregate supply is continuously matched with aggregate demand across all regions and all dispatch intervals. Second, it is responsible for coordinating transmission and ensuring dispatch schedules and unforeseen events do not constitute a reliability risk.

For the former, all generators within the NEM must be classified as either scheduled, non-scheduled or semi-scheduled depending on their relationship to the dispatch process. For each five-minute dispatch interval, AEMO balances electricity supply and demand. To balance the market, AEMO receives generation offers from scheduled participants and forecasts generation for all remaining participants. As such, scheduled generators are generally non-intermittent units above

30 MW. They are required to submit price-quantity offers and must comply with dispatch instructions. Semi-scheduled generators are intermittent generators above 30 MW. They are required to submit price offers, while AEMO predicts their generation via specific wind and solar forecasting models. Non-scheduled generators may be either intermittent or non-intermittent and have a nameplate capacity of 5 to 30 MW. These generators are not required to provide energy offers. AEMO predicts their generation, which is assumed as must-take and reimbursed at the appropriate market price.

AEMO uses a double-auction format within the spot market. After scheduled participants submit their offers, AEMO sets the market-clearing price and quantity at the intersection of the resulting aggregate supply curve and realized demand within each region. Generator bids consist of ten price-quantity pairs. The price bands must be increasing and are fixed the day before dispatch. Quantity bands can be submitted right up until dispatch. Essentially, generators have the flexibility to modify their bids until dispatch provided they can justify any changes under the good faith provision.[21]

For the latter, AEMO also operates markets for the acquisition of ancillary services (AS) or reserve capacity. AS are used to meet unexpected changes in the supply-demand balance and to adjust production in order to minimize congestion. Most reserve capacity is available within both the energy and AS markets. Given this overlap, AS markets likely impact the energy spot price and, therefore, should be considered in any market-wide modeling.

2.3.2. Market structure

The origins of the current electricity market structure stem in large part from the Hilmer Review (1993). Commencing in the late 1990's, the Review encouraged the privatization of many government-owned enterprises (GOEs) and the opening of generation and retail markets to competition. These changes occurred along with the formation of the NEM. However, since its inception, the NEM has been a concentrated market. This was noted early on by the Parer Review (2002), which emphasized how NEM outcomes could be adversely impacted by increased concentration

[21] The good faith provision obligates participants not to make false or misleading offers. This can otherwise be interpreted as any offer or rebid can and must not be changed unless there is also a change in the underlying material conditions upon which the offer or rebid is based.

Table 2.1. Capacity by fuel in 2019

Firm	Coal	Gas	Hydro	VRE	Other	Total
AGL Energy	7,295	1,727	678	1,718	80	11,498
Snowy Hydro	0	2,164	6,000	95	186	8,445
Origin Energy	3,000	2,606	240	970	499	7,315
EnergyAustralia	3,000	1,730	0	869	55	5,654
CS Energy	3,681	0	570	0	0	4,251
Stanwell Corporation	3,560	496	161	0	34	4,251
Hydro Tasmania	0	507	822	408	0	1,737
Engie	0	805	0	242	147	1,194
Other	3,955	2,121	140	5,282	662	12,160
Total	24,491	12,156	8,611	9,585	1,664	56,506

Note: All values in MW.

and limited competition. It highlighted the decisions by the NSW and QLD governments to create generation portfolios instead of independent generation plants as in VIC and SA. Since then, generation within the NEM has experienced significant horizontal re-aggregation. These concerns were revisited in many recent electricity market reviews, including: the Finkel Review (2017), the Retail Electricity Pricing Inquiry (ACCC, 2018), and the Electricity Market Monitoring Inquiry (ACCC, 2019*a*,*b*).

Table 2.2. Capacity by region in 2019

Firm	NSW1	QLD1	VIC1	SA1	TAS1	Total
AGL Energy	5,403	677	3,626	1,792	0	11,498
Snowy Hydro	5,149	0	3,015	281	0	8,445
Origin Energy	4,093	1,578	629	1,016	0	7,315
EnergyAustralia	2,435	93	2,775	351	0	5,654
CS Energy	0	4,251	0	0	0	4,251
Stanwell Corporation	96	4,155	0	0	0	4,251
Hydro Tasmania	0	0	94	100	1,543	1,737
Engie	78	0	0	1,117	0	1,194
Other	3,180	4,678	3,206	1,097	0	12,160
Total	20,433	15,431	13,344	5,754	1,543	56,506

Note: All values in MW.

Tables 2.1 and 2.2 display generation capacities within the NEM by major firm and, respectively, fuel and region. While the tables present results for 2019, they are indicative of the market structure across our period of interest starting in 2015. Also note that capacities are associated with traders and not necessarily owners. However, for the majority of plants, these are equivalent. The concentration ratio of the top three firms (CR_3) by capacity for the NEM is ranges between 48% and 50%. Thus, at the NEM-level, the market appears only moderately concentrated. Nonetheless, within individual regions, concentration is significantly higher: it ranges between 72% and 77% within NSW; 64% to 72% within QLD; 70% to 71% within VIC; 68% to 70% within SA; and, 100% within TAS.

Higher concentration at the regional level is a product increasing horizontal re-aggregation. Though, it is also an artifact of how the NEM was constituted; whereby, five independent electricity markets were connected by a small number of interconnectors. While all regions of the NEM are highly concentrated, there are differences between regions. In QLD and TAS, concentration is a result of government-owned companies controlling significant generation assets, including Stanwell Corporation, CS Energy, and Hydro Tasmania. In the other regions, private generation businesses together with Snowy Hydro control the majority of generation capacity.

2.3.3. Market power

Given the energy-only design of the NEM, it relies heavily on effective competition to deliver lower price outcomes. This is especially true given the limited set of rules governing how generators can bid into the market. Essentially, generators are only constrained by the price cap and the good faith rebidding provision. Neither of which prevent participants from exercising market power, that is their ability to raise prices above marginal costs (ACCC, 2018).

The benefit of a loosely-regulated, energy-only electricity market is the provision of clear price signals for the value of generation. Energy-only electricity markets are designed to arrive at the 'efficient' price for electricity supply, with the accepted drawback that occasional high price events are necessary for signalling when new capacity is needed (ACCC, 2019*b*). While generators rely on high price events to recover their fixed costs, in a competitive energy-only market, bidding their marginal cost is an optimal strategy as it maximizes dispatch. These features of the market design require competition among rival generators to drive efficient prices. Thus, while the energy-only design of the NEM means the market should deliver clear and efficient prices both for the short- and long-term, it is a design that is vulnerable to the exercise of market power.

Beyond the market design, there are a number of common factors which exacerbate the NEM's potential exposure to market power, including: a high price cap, inelastic demand and supply, transmission constraints, and repeated interactions. Unlike most US markets outside of Texas, the NEM's price cap is very high. Between 2015 and 2019, the cap grew from $13,500 AUD/MWh to $14,700 AUD/MWh.[22] For comparison, ERCOT – the market operator in Texas and the sole energy-only market in the US – stipulates a price cap of around $12,000 AUD/MWh. All other US electricity markets include some form of capacity payment and have much lower offer caps. The next highest one belongs to MISO at around $5,000 AUD/MWh. The higher cap in the NEM provides incentives for investment but also means that the short-term exercise of market power can be very profitable. Thus, combined with a high price cap, even short periods of market power can significantly increase average market costs.

Both electricity demand and supply are largely insensitive to price in the short run. For the former, load serving entities have limited control over customer demand since rates are typically invariant to wholesale prices. Their ability to reduce end-use demand is, therefore, limited in any given settlement interval. Moreover, the capacity to mitigate use through efficiency improvements is fixed in the short run. Similarly, the capacity to generate electricity is also fixed in the short run. Generators typically have limited scope to increase output when the wholesale price is high. As a result, when demand approaches the maximum capacity of the system, both the demand and supply curves become very steep. Thus, with little scope to reduce demand or to expand supply in the short-run, small changes in either can result in an increased potential for market power.

Transmission, particularly between regions, is critical for mitigating market power. Without binding constraints, out-of-region generators can offer supply to take advantage of higher prices in neighboring regions. For example, if prices in NSW consistently exceeded those in QLD, then cheaper QLD generators could be dispatched to meet demand in NSW. Thus, costs are minimized through the lowest cost generation meeting demand. Conversely, binding transmission constraints

[22] The NEM's market price cap is adjusted each 1 July for inflation. Over our period of interest, it was set to: $13,500 AUD/MWh for 2014-15; $13,800 AUD/MWh for 2015-16; $14,000 AUD/MWh for 2016-17; $14,200 AUD/MWh for 2017-18; $14,500 AUD/MWh for 2018-19; and, $14,700 AUD/MWh for 2019-20. The market price floor is set at -$1,000 AUD/MWh and is adjusted only when deemed necessary.

can limit the area over which generators compete, increasing the scope of local market power. This issue can be particularly acute in the NEM as it is a long and linear grid with limited network meshing. Thus, it is relatively easy for regions, particularly those at the ends of the NEM, to become islanded (Finkel et al., 2017). As such, constrained transmission both within and between regions can result in opportunities for the exercise of market power.

Finally, repeated interactions are well known to have the potential for establishing tacit cooperation or collusive arrangements. Within the NEM, generators interact with each other repeatedly in the dispatch process. Moreover, such interactions can be easily exploited in the NEM due to the fact that generators can adjust their bids right up until dispatch. While this potential does exist, no incidents of collusive behavior have yet been recorded in the NEM.

2.4. Queensland Government Involvement in the Generation Sector

Over the past 30 years, the Australian electricity sector has been substantially reformed, moving from public service delivery to a private contestable market. QLD was a founding member of the NEM, where its Government's choices at the inception of the market—particularly with respect to ownership and horizontal disaggregation—have had a lasting impact on the market itself, but also on the wider economic and political trends within the state. In this section, we review QLD's relationship with the NEM, including the debate over government ownership, the resulting market concentration, and finally, the consequences for strategic behavior within the generation sector.

2.4.1. Government ownership

Australian governments began to reform the electricity industry in the 1990s. In the early part of the decade, the Independent Committee of Inquiry into a National Competition Policy for Australia recommended the introduction of competitive market arrangements within the industry (Hilmer, Rayner and Taperell, 1993). These findings led to the reforms under the National Competition Policy Reform Act 1995 and the related Competition Principles Agreement, precipitating the development of the NEM. Historically, the electricity industry operated as vertically-integrated, public utilities with limited physical interconnection between state grids (Parer, 2002). Individual state agencies were responsible for planning, developing, commissioning and operating the electrical grid, while governments owned and operated the electricity supply chain from generation through to retailing.[23] Before the reforms, economic considerations were secondary to technical requirements. The NEM placed economic and market considerations on an equal footing with supply availability and reliability—the traditional drivers for the government-owned electricity sector.

In 1996, the Eastern mainland states and territories—including the ACT, NSW, QLD, SA and VIC—agreed to pass the National Electricity Law, which provided the legal basis to create the NEM (AER, 2009). This involved the introduction of a compulsory, competitive wholesale market for the trading and dispatch of electricity. It necessitated the separation of the vertically-integrated electricity supply chain and the horizontally-integrated generation sector.[24] Structural reform of public electricity utilities was undertaken prior to the market commencement in December 1998. All participating states mandated the horizontal disaggregation of generation into separate and competing business units within their jurisdiction.

Within QLD, the Electricity Industry Structure Task Force reported to the state Government on structural, institutional and regulatory changes to the electricity supply industry in late 1996 (Roarty, 1998). Shortly thereafter, the QLD Government announced its electricity reform strategy: "Powering the Future" (QLD Government, 1996). At the time, the state industry was characterized by a dominant government-owned generator—known as AUSTA Electric—and a monopoly government-owned transmission, distribution and retail corporation. Under the reform strategy, the industry was restructured from July 1997 in preparation for the introduction of the NEM (Rann, 1998).[25] The QLD Government split AUSTA Electric, which was responsible for around 80 percent of the state's electricity,[26] into three independent government-owned generating companies: CS Energy, Stanwell Corporation and Tarong Energy.[27] Unlike the SA and VIC Governments, which

[23] Vertically-integrated electric utilities include generation, transmission, distribution and retail businesses.

[24] In addition, the creation of the NEM involved the staggered introduction of retail competition. It also brought monopoly transmission and distribution networks under both access and economic regulation.

[25] While QLD was part of the NEM from its inception, it was not physically connected with the market until two interconnectors—Directlink in April 2000 and QNI in February 2001—linked the QLD and NSW regional networks (AER, 2009)

[26] The remaining 20 percent was provided by independent power producers.

[27] Prior to the restructure, other alternatives for introducing competition to the generation sector were considered, including: encouraging new private generators; relying on intra-region generators; and, a robust regulatory approach (QLD Government, 1996).

both disaggregated and privatized their generation businesses, the QLD Government enacted only the former. As wholesale electricity prices would no longer be set by the Government, the AUSTA restructuring was justified as a means to limit market power, to engender cost efficiency discipline, and to encourage private entry (QLD Government, 1996).[28] Moreover, it was argued, these changes would ensure consumers benefited from the enactment of national competition reform through lower costs and prices.[29]

While the three new generation companies were deregulated and granted corporate autonomy, they remained government-owned with the Treasurer and the Minister for Energy as shareholders. The reasons for maintaining government control were fourfold. First, the creation of the NEM was intended to spur deregulation and not necessarily privatization. Within broad parameters, it was left to each jurisdictional government for how best to restructure their electricity assets.[30] Second, the QLD Government wished to maintain options in the face of uncertainty. At this early stage, the long-term success of the NEM was not assured, nor were asset sales necessarily beneficial for taxpayers. As such, the Government hedged their bets and left open the possibility of unwinding deregulation or pursuing privatization in the future.[31] Third, the QLD Government wished to maintain the dividends received from the various segments of the electricity supply chain. Within the Government at the time, ownership and dividends were viewed as the preferred option over a sale and a one-time windfall.[32] Finally, the QLD Government sought to establish strong competitors within the NEM.[33] Implicit in this argument was, to the extent possible, the desire

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[28] As argued by Gilmore (1997*a*): "[the] major elements of the reform agenda establishing effective competition in generation by splitting AUSTA Electric into three independent and competing Government-owned generators ... will prevent the incumbent monopoly generator from using its market power to manipulate the market and will also provide maximum opportunity for privately owned generators to enter the industry."

[29] As stated by Gilmore (1997*a*): "as the owner of these significant [electricity] assets, the Government must ... restructure the industry to ensure that Queensland is able to deliver low cost electricity."

[30] Gilmore (1997*b*): "[t]he objectives ... relate to the deregulation of the electricity industry and the efficiency of the electricity industry in respect of our joining the national grid in early 2001."

[31] Gilmore (1997*b*): "[t]his Government's policy in respect to privatisation of the electricity industry is that privatisation is not an issue at present ... [This] Government cannot entrench changes to the electricity industry so that future Governments do not have options available to them in terms of privatisation, corporatisation or unwinding."

[32] Gilmore (1997*a*): "I emphasise that these reforms do not involve the privatisation of any of the Government's existing electricity industry assets. Rather, as the owner ... the Government must ... deliver ... a commercial rate of return to [the public] on these assets ... The accountability of the electricity corporations to Government and the Parliament will in no way be diminished."

[33] Gilmore (1997*b*): "we now have to set in train various processes which will ensure that, when we join the national grid, we do so as real competitors."

to leverage ownership and maximize dividends. This is consistent with the establishment of a few generating companies each with a portfolio of assets, in lieu of power plants competing as individual companies. While not explicitly stated, there may have been an incentive for the Government to restructure the electricity industry as a set of government-owned oligopolists capable of delivering sufficient rates of return.

Almost as soon as the decision to limit restructuring at deregulation was taken, it came under scrutiny. The CoAG Independent Energy Review Panel released a report titled "Towards a Truly National and Efficient Energy Market," otherwise known as the Parer Review (2002). The Review criticized the structure of the generation sector in QLD and concluded that it did not support competitive outcomes. At the time, the three largest generating companies—all publicly owned—comprised around 70 percent of total QLD capacity. When considering all government-owned corporations, public control of generation represented over 85 percent of capacity. The Panel noted that QLD could rectify undue regional concentration of ownership by further disaggregating their portfolio generation businesses.[34] This would create more competitive regional markets and minimize the risk of any generator being able to exercise market power. This was followed in 2006 by the "Queensland Energy Structure Review" which provided recommendations to the QLD Treasury (BCG, 2006). The Review proposed that the Government divest its generator assets to avoid commercial and market risks. The former related to declining wholesale electricity prices, while the latter were associated with the risk of crowding out private sector investment.

Despite the intense political pressure, the QLD Government resolved to keep its generating assets in public hands. In fact, the Government twice further consolidated its generation holdings. In 2007, it transferred the remaining fossil-fired assets from the government-owned network business—Enertrade—to both CS Energy and Stanwell (QLD Government, 2007*a*).[35] In 2010, the Government restated its commitment to public ownership of electricity generation assets through the "Shareholder Review of Queensland Government Owned Corporation Generators"

[34] The Panel also singled out NSW as another region suffering from high concentration due primarily to large government-owned portfolio generators.

[35] Collinsville Power Station was transferred to CS Energy, while Gladstone Power Station was transferred to Stanwell. The increased public consolidation was somewhat offset by private sales: Enertrade's Oakey Power Station to AGL (AGL, 2007); and, wind assets from Stanwell and Tarong to Transfield Services Infrastructure Ltd. QLD Government (2007*b*).

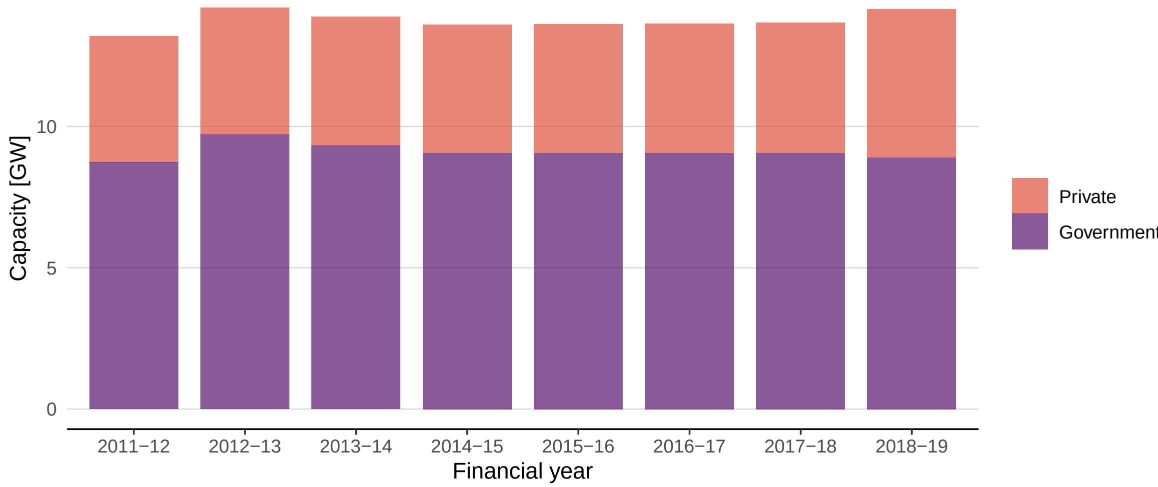
(QLD Government, 2010).[36] Furthermore, despite the concerns of the ACCC (2018), it consolidated its three generation companies into two. Tarong Energy became a subsidiary of Stanwell from July 2011. This left CS Energy and Stanwell as the sole government-owned generating companies and the dominant market participants within QLD. The Government argued that an unfavorable supply-demand balance and market developments—including, the emergence of vertically-integrated gentailers and imminent carbon pricing legislation at the national level—necessitated a restructuring to ensure its assets could adequately compete in the NEM (QLD Government, 2010). Moreover, public participation in the market did not appear to prevent private sector investment, as QLD had experienced the largest capacity expansion of any NEM region (AER, 2011*b*).

In 2012, the Liberal National Party won power in QLD for the first time since the inception of the NEM, replacing the Labor Party. The following year, the new Government examined the potential costs, risks and benefits of divesting Stanwell and CS Energy, as recommended by a Commission of Audit (Costello, Harding and McTaggart, 2013). The Commission argued that the government-owned generators suffer a competitive disadvantage through conflicting non-commercial policy and regulatory requirements. They went on to state that delivery of government policy objectives through ownership in the electricity industry is inefficient and lacks transparency. They also attacked the notion that the disposal of assets denies the Government the benefit of future dividends. By association, the Commission noted that holding assets subjects the Government to the risk of commercial or political factors eroding the value of those same dividends. Finally, they mentioned the opportunity cost of locking up scarce capital to the detriment of higher priority uses to meet core government priorities.

Leaning on the Commission's recommendations, the Government released its electricity industry strategy titled "PowerQ" (QLD Government, 2014). The policy proposal included plans to lease CS Energy and Stanwell for 50 years, with options to extend for a further 49 years (AER, 2015*e*). At the same time, the Government reiterated that no sale would proceed without a mandate from the QLD electorate.

[36] As elaborated by Fraser (2010): "[t]he government resolved in 2006 to maintain public ownership of the generators, and this review has not altered that position. The continued ownership of the baseload fleet is a matter of settled policy for this government. The outcomes of the review will keep the generators in public ownership but restructure them to meet the challenging markets they now face."

FIGURE 2.1. Government vs private capacity ownership within QLD by financial year.



Notes: This plot presents government versus private generation capacity ownership in QLD between the 2011-12 and 2018-19 financial years. The capacities for each bar are based on a snapshot taken on the first day of the new financial year, 1 July. Ownership is based on trading rights defined by the AER. Within QLD, ownership and trading rights are effectively the same, since the vast majority of government companies schedule the units that they own. Since the PowerQ restructure, government-owned generators have maintained at least 60% of the total capacity within QLD.

In early 2015, the Labor Party returned to power, partly under a promise to keep electricity industry assets in public hands.[37] Following the change of government, PowerQ and the generator privatizations were scrapped.[38]

Thus, the 2011 restructure policy, consolidating generator assets into two government-owned portfolios, persisted. Originally, this policy aimed to refocus the corporate strategies of the government-owned generating companies from business development and growth to one of operational efficiency across the existing asset base (QLD Government, 2010). At the time, it was anticipated this strategy would result in a reduced market share, as additional capacity requirements

[37] As summarized by Bailey (2015): "The state election delivered a verdict from Queenslanders on the future of our electricity industry. The No. 1 message was no asset sales. The [Liberal National Party] went to the election urging Queenslanders to sell every part of our electricity industry to the private sector. They [said the Labor Party treats] it like a cash cow, yet their policy was to take the energy companies to the abattoir. Every generator, every transmission line, every pole, every wire, every regional depot and every meter in every home was to be sold off to the highest bidder."

[38] The Labor Party's election platform was to merge the remaining state owned generators—CS Energy and Stanwell—into a single government-owned company. Structural reform was considered as a mechanism for improving business practices and realizing cost savings. This, however, never came to pass due to pressure from the ACCC (Ludlow, 2015) and the state's own Productivity Commission (2016).

associated with rising demand would be met by the private sector (Commission, 2016). The QLD Government considered that the approach would establish clear conditions for future investment in the sector, providing the private sector with confidence to invest in timely new capacity. Since the restructure, however, there has been no private sector investment in new NEM-connected generation capacity in QLD. As can be seen in Figure 2.1, the market share of the government-owned generating companies has not fallen as was predicted.

2.4.2. Market concentration

Market concentration in the NEM has always been high (ACCC, 2018).[39] The resultant impacts on market outcomes were noted as far back as the Parer Review (2002). The Review lamented persistent concentration throughout the market and admonished the QLD Government, in particular, for its decision to create three government-owned generation portfolios in lieu of further disaggregation.[40] Since that time, significant horizontal re-aggregation of the capacity in QLD has occurred, where publicly-owned generation was primarily responsible.[41] The state's wholesale electricity market has been persistently concentrated and isolated (AER, 2015*e*). It has less interconnector capacity than either NSW or VIC and this, in conjunction with the high concentration of generation ownership, means that producers have a greater opportunity to exercise market power (Wood and Blowers, 2018). This increases generator revenue above what would occur in a competitive market. It allows generators to collect market power rents, thus, reallocating surplus from consumers to producers and causing deadweight loss.

Since the 2011 restructure in QLD, the state's spot market has been subject to increasing prices and occasional periods of increased volatility. The drivers of these outcomes are myriad; however, many stakeholders—including legislators, regulators and participants—acknowledge that highly concentrated markets have exacerbated the situation (AEMC, 2015*a*,*b*; Commission, 2016). The

[39] In electricity-only markets—like the NEM—some degree of concentration and market power is necessary due to the "missing money" problem. See Joskow (2013) and Newbery (2016).

[40] The Parer Review (2002) also cautioned that the nature of generating units controlled by portfolio generators may strengthen the potential for them to exercise market power Parer (2002).

[41] While all regions of the NEM are highly concentrated, there are differences between them (ACCC, 2018). In QLD and TAS, concentration is a result of government ownership of significant generation assets. In the other NEM regions, it is commercial gentailers together with government-owned Snowy Hydro which have the majority of generation capacity.

AER stated that CS Energy and Stanwell—the two government-owned participants—can exercise market power due to their dominant market positions (AER, 2018*c*).

Along with high concentration, the adverse market outcomes in QLD have been attributed to a tightening of the supply-demand balance and changes in the cost of generation (ACCC, 2018; Commission, 2016). For the former, reduced supply and increased demand caused an increase in competitive rents. Within QLD, the government-owned generators mothballed capacity at Tarong Power station in 2012 and Swanbank E in 2014. The wider NEM experienced the exit of low-cost brown coal generation, including Northern Power Station in 2016 and Hazelwood Power Station in 2017. The rising demand for electricity in QLD was largely driven by the start-up of the LNG projects near Gladstone. For the latter, the underlying factors of production became more expensive, in particular due to increases in fuel costs. With respect to black coal, international prices began to rise, while NSW generators suffered from supply disruptions. The increase in gas prices was largely due to competing demands from LNG exports, exposing domestic gas to international prices, and declining sources of domestic supply (ACCC, 2018). Thus, increased concentration alone is unlikely to have instigated the adverse market outcomes in QLD. It is, nonetheless, a contributing factor to both their frequency and magnitude.

2.4.3. Strategic behavior

Since the 2011 restructure, regulators have identified three market behaviors of the QLD government-owned generators which have exacerbated deleterious market outcomes, namely: strategic congestion, strategic rebidding and shadow pricing.

Strategic congestion refers to an interplay of opportunistic bidding and transmission network congestion which led to spot market volatility in QLD between August and October 2012 and again in January 2013 (AER, 2013*b*). In the 2011 restructure, CS Energy acquired control of the generation at both ends of a strategic transmission line in central QLD.[42] Thereafter, its bidding behavior periodically resulted in power flows that contributed to network congestion. CS Energy could cause a constraint to bind by increasing northerly flow along the bounded line. This was

[42] CS Energy operated the Callide and Gladstone Power Stations located at southern and northern ends, respectively, of the Calvale-Wurdong transmission line.

possible by increasing output at the southern end, reducing output at northern end, or both (AER, 2012). Given the flexible rebidding rules within the NEM, CS Energy could manipulate its dispatched capacity between the two plants at short notice.[43] With the constraint binding, AEMO was obliged to manage the issue by 'constraining off' low cost generation in southern QLD and 'constraining on' high cost generation north of the congested line. [44] As a consequence of the zonal nature of the NEM, the exchange of low- for high-priced QLD generation lead to increased within-region prices and volatility.[45] By late 2013, the construction of a nearby transmission line eliminated the possibility of strategic congestion (AER, 2015*e*).[46]

The QLD government-owned generators adopted another bidding strategy: strategic rebidding. The behavior was exploited by both by CS Energy and Stanwell and caused high prices and volatility during the summers of 2013 to 2017 (AEMC, 2015*a*; AER, 2014*b*, 2015*e*, 2017*d*, 2018*b*).[47]

Rebidding provisions trade off dispatch efficiency and competitive outcomes (AER, 2018*c*). In the short term, rebidding promotes efficient dispatch as it allows the market to respond dynamically to changing conditions and/or information. Over the long term, rebidding indirectly supports efficient investment decisions. Efficient wholesale prices provide the best signal for investment, both in terms of the quantity and type of generation capacity needed over time. However, some forms of rebidding can be detrimental to competition and efficiency. Rebidding unrelated to genuine market conditions can limit or deter other participants from providing a competitive response. In QLD, these behaviors compromised the efficiency of dispatch, causing prices to spike independently of underlying market conditions (AER, 2014*b*). Spot price volatility increases market uncertainty. In the short term, this puts upward pressure on forward contract prices and, ultimately, flows

[43] In essence, CS Energy could increase flow on the Calvale-Wurdong line by rebidding capacity at Callide into lower price bands or capacity at Gladstone into higher ones. Moreover, if the change in offer price was accompanied with a high ramp rate then the change in dispatch level could be rapid (AER, 2012).

[44] AEMO was also forced to send power flows out of QLD into NSW, often contrary to price signals—that is, electricity flowed from the higher priced QLD region to the lower priced NSW region (AER, 2012).

[45] The price volatility was largely driven by participant bidding behavior in response to the unexpected congestion. This problem was known as disorderly bidding—that is, bidding contrary to underlying generation cost structures and/or technical characteristics (AER, 2013*b*). In particular, generators tried to maintain output levels and receive high spot prices by rebidding capacity from high to low—or even negative—prices. They also rebid down their ramp rates so they could be constrained off only slowly.

[46] Despite resolving the congestion, planners resorted to a costly technical solution. Other options, including shareholder intervention, rule changes, restructuring, etc., may have been less expensive.

[47] The rebidding provisions within the National Electricity Rules have been contentious since the NEM's inception. During the Parer Review (2002), stakeholders were critical and claimed that rebidding strategies had allowed the exercise of market power by generators.

through to consumers' electricity bills (AER, 2015*e*). Over the long term, such market conditions can deter new private investment in capacity.

Strategic rebidding was typically used in QLD on days of high temperatures and high energy demand, and often when import capability on transmission interconnectors was limited—that is, periods where there was a tight supply-demand balance (AER, 2015*e*). Nevertheless, leading into the events, demand and generation plant availability were usually within pre-dispatch forecasts, and price spikes were not predicted (AER, 2014*b*). Given these conditions, generators would periodically rebid capacity from low to high price bands late in a settlement interval. The bids were typically short-lived, lasting for only one or two dispatch intervals. In tight market conditions, though, even such bids are able to cause prices spikes if other generators lack sufficient time to respond to the rapid unexpected shift in supply. The probability that a late rebidding strategy is commercially successful increases in an environment where the supply and demand balance is tight and/or ownership is concentrated (AEMC, 2015*a*). The asymmetric dispatch and settlement interval lengths further enhanced the profitability of such opportunistic bidding: a price spike in one 5-minute dispatch interval that instigate a high 30-minute settlement price allows generators to rebid capacity late and capture high prices for their generation across the associated settlement interval.[48]

To recap, three main factors contributed to strategic rebidding in the NEM (Wood and Blowers, 2018). First, market rules which permitted late rebids, when few, if any, generators could respond. Second, the inability, or unwillingness, of participants to respond rapidly to unexpected market conditions. Third, highly concentrated generation ownership which allows for the exercise of market power.[49]

The first two factors were addressed through a series of market rule changes. In July 2016, the AEMC adopted reforms related to the integrity of bidding behavior in the NEM: bidding in

[48] Further discussion of strategic late rebidding as well as specific events in QLD can be found in reports titled "Electricity spot prices above $5,000 per MWh" prepared by the AER (2013*a*, 2014*a*, 2015*a*,*b*,*c*,*d*, 2017*a*,*b*). For instances when prices are below $5,000 per MWh, see Wood and Blowers (2018), who develop a methodology for systematically estimating settlement intervals containing late rebidding. The AEMC (2018) provides a critique of their methodology and analysis.

[49] The AER (2018*c*, p. 36) noted: "Participants ... have exercised market power at times in the past five years, but it has not been sustained. Opportunistic rebidding by some QLD generators caused periods of spot price volatility between 2013 and 2016."

good faith (AEMC, 2015*a*) and generator ramp rates (AEMC, 2015*b*).[50] Similar to the original, the revised bidding in good faith provision aimed to mitigate the number of false or misleading bids made by market participants.[51] It then went further by requiring rebids to be made as soon as practicable after a material change in conditions and to record the circumstances surrounding any late rebids.[52] The revised ramp rate provision aimed to promote efficient dispatch by allowing the market to respond efficiently to a change in merit order. The specific reforms applied the then existing ramp rate limits to individual physical units within aggregated generation facilities. In doing so, they effectively raised the minimum aggregate ramp rate capability across the NEM by around 30 per cent (AER, 2017*d*).

Late rebidding declined after the AEMC initiated the rule change processes in 2014 (AER, 2018*c*). This suggests that regulators were able to have decrease attempts by QLD government-owned generators to exercise market power through regulatory aversion. Moreover, after the rules were implemented in July 2016, the government-owned generators changed rebidding strategies. Instead of shifting capacity to high price bands and causing high prices, they reverted to shifting capacity to low price bands during settlement intervals with high RRPs (AER, 2018*c*). While the rule changes clearly influenced behavior, they did not result in lower QLD wholesale prices, especially during the summer of 2016-17.

The increased prices in 2016-17 were a result of a sustained increase in offers, rather than temporary price spikes as is typical with strategic rebidding (AER, 2018*b*). During this time, the QLD government-owned generators along with other coal-fired producers adopted a shadow pricing strategy. This resulted in less price volatility but higher average prices AER (2018*c*). In a competitive market, generators have an incentive to bid at their marginal cost—the cost of

[50] Additionally, the AEMC (2017) addressed dispatch and settlement asymmetry by adopting 5-minute settlement intervals. The associated rule was implemented in July 2021 and, as such, is outside the scope of our paper.

[51] The bidding in good faith reform was precipitated by a Federal Court decision handed down in August 2011 in relation to proceedings the AER took against Stanwell Corporation. The AER alleged that Stanwell had breached the good faith provision through a series of rebids in February 2008 (AER, 2008). The Federal Court dismissed the case (AER, 2011*a*), and the event became a harbinger for similar strategic rebidding by the QLD government-owned generators between 2013 and 2017. The revised rules came about as there existed concern that the Federal Court decision had introduced uncertainty over the provision's original policy intent and highlighted issues in relation to its implementation (AER, 2018*c*).

[52] The rule change defined a 'late rebidding period' as 15 minutes before a trading interval starts and the period of the trading interval itself AER (2018*c*). If a rebid is made within this late rebidding period, then the participant must keep contemporaneous records, which the AER can request to ensure the rebid was not false or misleading.

producing an extra unit of electricity. If they bid a higher price, they risk not being dispatched and, therefore, not receiving any revenue. If they bid a lower price, they can potentially lose money on the electricity they produce (Wood and Blowers, 2018). When a generator with high marginal costs sets the price, all other generators benefit from additional revenue. Coal-fired units, representing baseload, are typically lower in the merit order, such that they are dispatched more often than not. If marginal costs for higher merit order plants increase, then coal units can increase their offers without fear losing dispatch. This "shadowing" of the next highest unit is where the name for the strategy originates.[53] So while generator behavior changed as a consequence of the AEMC reforms, the adoption of shadow pricing meant that the new rules did not lower market prices (AER, 2018*c*).

A number of factors contributed to the use of shadow pricing by QLD government-owned generators. Gas prices increased significantly in the preceding years, increasing in turn the cost of gas-fired generation which is typically above coal in the merit order and acts as an upper bound to their offers.[54] Moreover, changes in NEM-wide supply conditions contributed significantly to the sustained uplift in prices. A large amount of low cost capacity exited the market. This included the abrupt exits of Hazelwood and Northern Power Stations—sizable brown coal plants in VIC and SA, respectively. Moreover, NSW black coal generators experienced coal supply issues and responded by offering their capacity at higher prices. A weaker competitive environment allowed QLD black coal—a lower-cost generation source—to offer capacity at higher prices (ACCC, 2018; AER, 2018*c*).[55] Given the lack of competitive constraint in the NEM at-large, the divergence between QLD government-owned generators' offer prices and their fuel costs along with the resulting high prices were likely exacerbated by the highly concentrated market structure in QLD (ACCC, 2018).

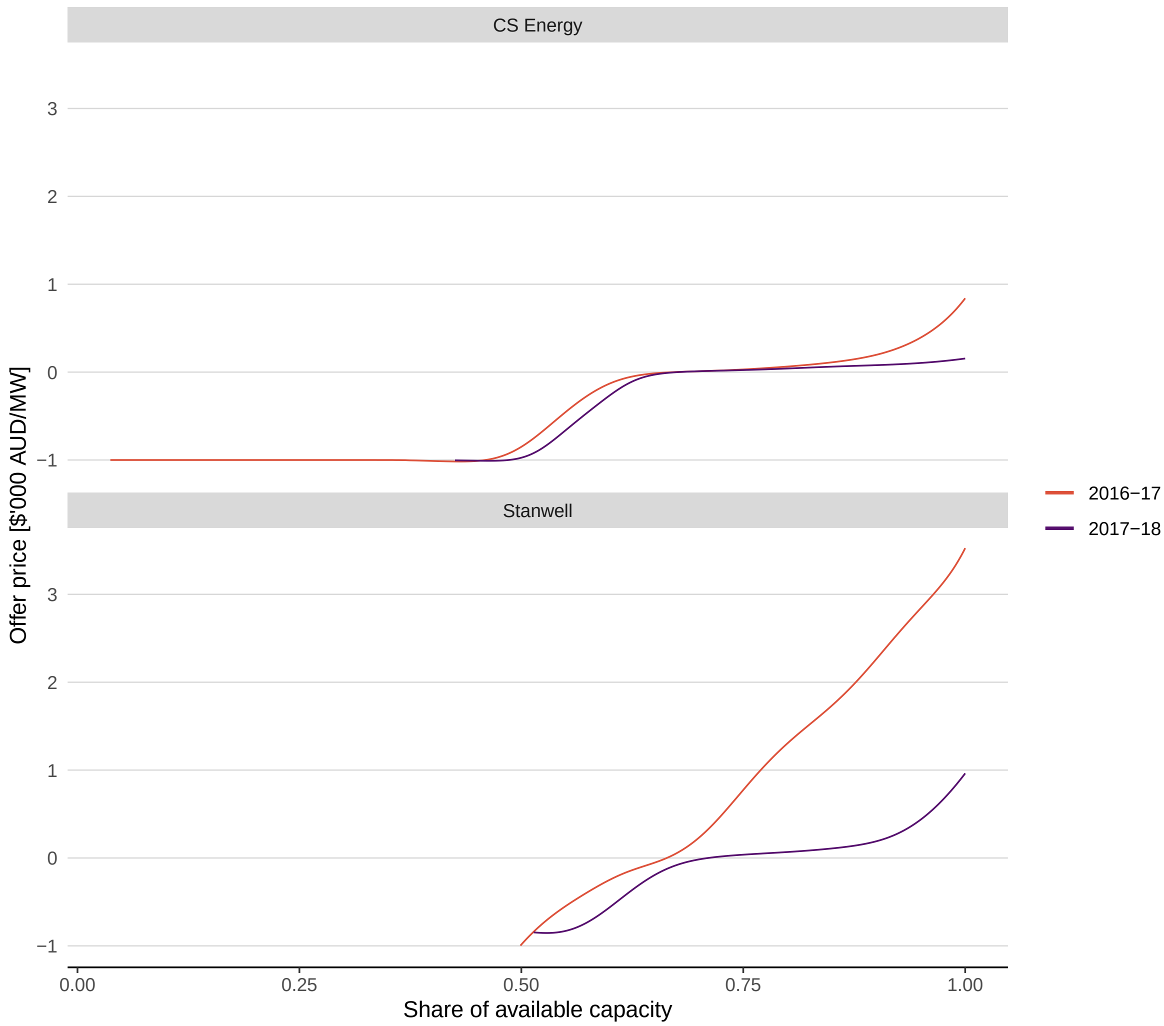
The QLD Government, in June 2017, "directed Stanwell to alter its bidding strategies to help put as much downward pressure on wholesale electricity prices as possible" (QLD Government,

[53] Shadowing behavior is not illegal; in fact, it is commercially rational. If generators are able to earn higher profits through shadowing behavior, it can create market signals for investment in new generation (Wood and Blowers, 2018).

[54] Increases in gas offers were adjudged by the ACCC (2018) to be in line with increases in gas fuel costs.

[55] An alternative possibility is that fuel prices for QLD black coal generators also increased. However, the ACCC (2018) found that the weighted average fuel cost for QLD black coal generators declined between 2015 and 2018. It could also be the case that they were exposed to international coal prices at the margins, and thus, their opportunity cost of coal for electricity generation was also exposed AER (2018*c*). This could have affected their offers, though such increases in fuel costs are unlikely to explain the entire increase in RRPs.

Figure 2.2. Normalized offer curves by government-owned company and financial year.



Notes: This plot presents average relative offer curves for CS Energy and Stanwell during the 2016-17 and 2017-18 financial years. The 2016-17 financial year curve occurred prior to the QLD Government's "Stanwell Direction." The curves are local polynomial regressions using a normal kernel with a 0.04 bandwidth. Some curves do not extend back to zero on the quantity axis since there are no no points in those areas. It should be assumed that all curves extend back horizontally until (0, -1,000).

2017*b*).[56] Stanwell indicated it subsequently adjusted its bidding behavior in line with the direction. Despite record demand, wholesale prices in QLD were significantly lower and price volatility was

[56] As stated by the Premier (Palaszczuk, 2017): "We can intervene to reinvest the dividends of our power companies because we own the assets. Now, under the Powering Queensland Plan, we can go further—because we own the generators. We are directing Stanwell Corporation to take action during extreme weather events that puts downward pressure on power prices."

down during the summer of 2017-18 following the direction (AER, 2018*b*).[57] Market intervention by the QLD Government played a key role in this outcome, while Stanwell Corporation's bidding was also a key driver.[58] In the summer periods of 2015-16 and 2016-17, Stanwell offered significant quantities at high price levels, which coincided with very high wholesale prices during those summer periods. The significant change in their bidding strategy can be observed in the bottom panel of Figure 2.2. During 2016-17, the top fifth of their available capacity was offered on average at prices above $1,000 AUD per MW. During 2017-18, none of their available capacity was offered above that price on average. CS Energy was not subject to the direction, though it also adjusted its bidding behaviour (ACCC, 2018). It offered significant capacity at its Gladstone Power Station at high prices prior to the direction to Stanwell. Similar to Stanwell, after the direction was issued the amount of capacity it offered at high prices reduced. This can be seen in the top panel of Figure 2.2. The changes in bidding strategy for Stanwell and CS Energy contrast with those in other regions, where there is not much difference between the average curves during financial years 2015-16 and 2016-17. See Figure 2.C.1 in Appendix 2.C which shows offer curves at the region level.

The ACCC (2018) concluded that, in the absence of the direction by the QLD Government to place downward pressure on wholesale prices, there was very limited constraint on the bidding behavior of QLD government-owned generators. The AER (2018*c*) noted that their strategic behavior was reduced by the AEMC rule changes and effectively ended in mid-2017 through intervention by the QLD Government. The government direction remained in place until June 2019.

2.5. Competitive Benchmark Model

Within electricity markets, the difference between price and marginal cost of the most expensive unit required to meet demand is the fundamental measure of market power.[59] Assuming no market power, the absence of non-convexities, and a lack of other distortions, all units with a

[57] In fact, QLD went from having some of the highest average prices in the NEM to generally having the lowest average price. As stated by Bailey (2017): "Actions under the Powering Queensland Plan include ... [directing] Stanwell to adjust its bidding to maximize outcomes in the energy market ... What impact did that announcement have? A 10 percent drop in the future wholesale price within 24 hours."

[58] Other contributing factors to lower QLD RRPs included the government directed return to service of the mothballed Swanbank E generator—a gas-fired unit operated by Stanwell (QLD Government, 2017*b*).

[59] In markets with scarcity pricing, the proper measure of market power would be constructed based on bids and not prices.

marginal cost below the market price produce. Nonetheless, a naive comparison of the market price to the marginal cost of the marginal unit may not be an accurate measure of market power. Economic withholding – a firm strategically reducing output or raising its offer price – necessitates the replacement of its production by other, more expensive generation that may be produced by nonstrategic units. Therefore, to generate a reliable measure of market power, we must estimate the system marginal cost of serving a given demand if all firms were behaving as price-takers. In the following subsections, we describe the assumptions and data used for our competitive benchmark model and for generating estimates of the system marginal cost of supplying electricity in the NEM. We provide a synthesized description of our model in Appendix 2.A.

To construct a model of the NEM under perfect competition, we assume wholesale electricity is a homogeneous commodity and all units act in a manner consistent with perfect competition.[60] Finding the equilibrium solution based on a perfectly competitive market is identical to maximizing total welfare. Thus, for each time period $t \in \{0, \ldots, S\}$, a perfectly competitive market outcome is obtained by solving the following welfare maximizing problem:

$$\max_{q_{i,r,t}} W_t = \sum_r \sum_i \Big[P_{r,t}(Q_{r,t}) - c_{i,r,t} \Big] \cdot q_{i,r,t} \tag{2.1}$$

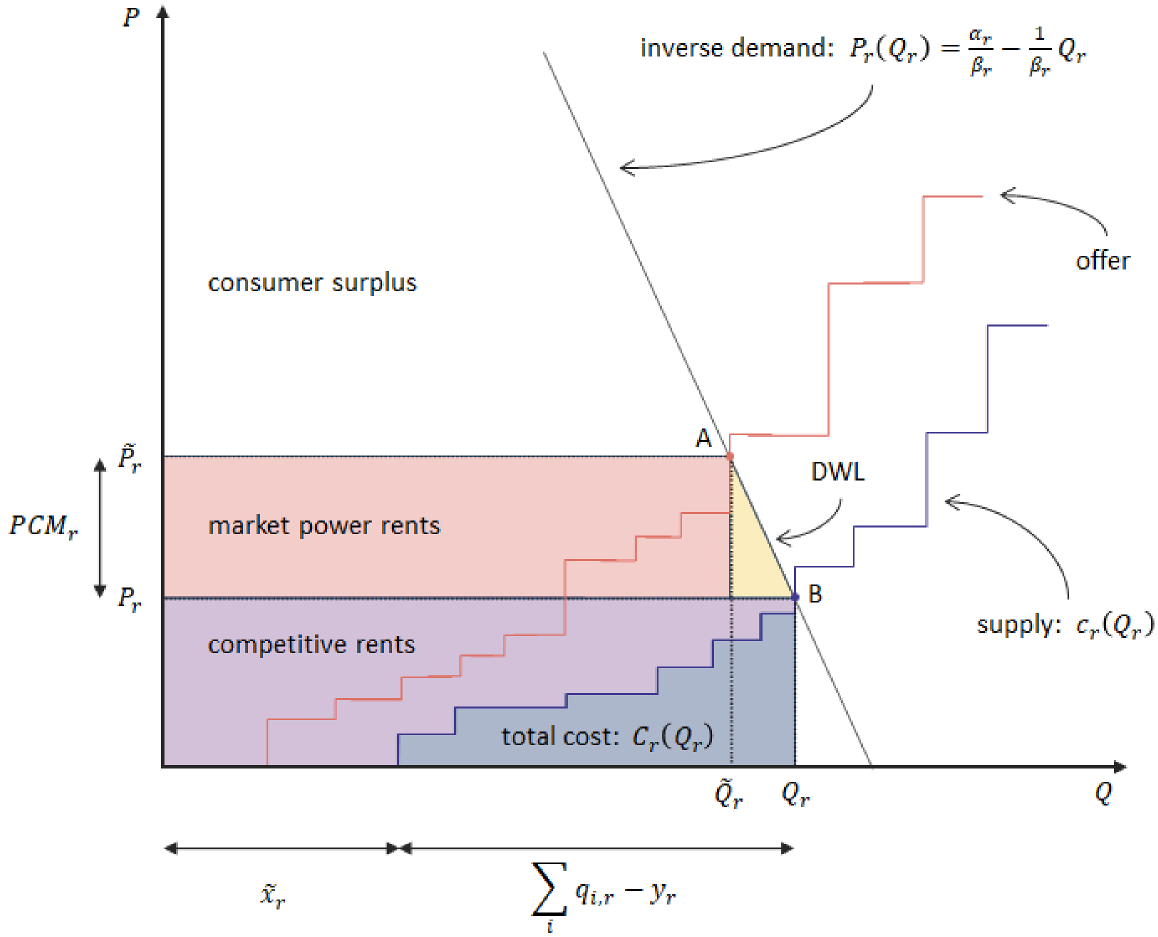
where the output of unit i from region r at time t is represented by $q_{i,r,t}$ and is limited by its capacity: $q_{i,r,t} \leq \overline{q}_i$. Simulated regional prices for region r and period t are given by $P_{r,t}(Q_{r,t})$, and simulated regional market demand by $Q_{r,t}$. Marginal costs are defined as $c_{i,r,t}$ and are unit- and time-specific. Figure 2.1 summarizes the maximization problem visually, while the following subsections address its various components.

2.5.1. Market demand and prices

We use the generation of fossil-fired units $q_{i,r,t}$ to construct the residual demand for electricity within each region. Thus, our estimate of the demand does not represent full end-use demand, but instead the portion of demand satisfied by price-following generators. In effect, we assume the

60 This assumption can be relaxed such that our simulation approach uses a different benchmark, e.g. Cournot competition. Thus, our approach is capable of representing imperfect competition in the product market, see e.g. Bushnell, Mansur and Saravia (2008).

Figure 2.1. Welfare maximization problem for region r.



Notes: The diagram presents a visual representation of the welfare maximization problem for our simulated competitive benchmark model solved for each region r and settlement interval t. The price-cost margin, PCM_r, is equal to the difference in the actual and simulated market prices. The areas as drawn are defined in relation to the actual market equilibrium, point A. At the simulated equilibrium, point B, consumer surplus includes both the market power rents and deadweight loss (DWL) areas. Welfare W_r in the simulated model is, therefore, equal to the sum of the areas for consumer surplus, market power rents, competitive rents, and DWL. Both the offer curve and the inverse demand curve are sourced from actual market outcomes, while the supply curve is from the simulated model. We drop the t subscript for brevity. All remaining variables are as defined in the text.

operations of non-modeled units—e.g., hydro and renewables—is exogenous. The validity of this assumption is further discussed below.

Demand, as defined above, is represented by the function $Q_{r,t} = \alpha_{r,t} - \beta_r P_{r,t}$ for each region r and time period t. It yields an inverse demand curve defined as:

$$P_{r,t}(Q_{r,t}) = \frac{\alpha_{r,t} - \sum_i q_{i,r,t} - \tilde{x}_{r,t} + y_{r,t}}{\beta_r} \tag{2.2}$$

where $\tilde{x}_{r,t}$ represents must-take generation and $y_{r,t}$ is net injections into region r.[61] The intercept, $\alpha_{r,t}$, and slope, $\beta_{r,t}$, of the demand function is time-dependent since it is based upon actual demand in each region. That is, we model a linear demand curve passing through the observed price–quantity pairs across each region and period: $\alpha_{r,t} = \tilde{Q}_{r,t} + \beta_{r,t} \cdot \tilde{P}_{r,t}$, where tildes signify actual market outcomes.[62] In the short-run, electricity is an extremely inelastic product, resulting from consumers lack of exposure to wholesale prices and an inability to shift demand to other energy sources or times. Thus, we set the price elasticity of demand to a low value: $\varepsilon = -0.1$.[63] The slope of the demand curve is, thus, estimated as: $\beta_{r,t} = \varepsilon \left(\frac{\tilde{Q}_{r,t}}{|\tilde{P}_{r,t}|} \right)$

The components of demand deserve some additional discussion. Essentially, we define demand as equivalent to the sum of fossil-fired generation, must-take generation, and imports: $Q_{r,t} = \sum_i q_{i,r,t} + \tilde{x}_{r,t} + y_{r,t}$. Note that must-take generation includes hydro, variable renewables (i.e. solar & wind), batteries, non-scheduled generation, and AS. Each of these elements and their components will be further elaborated below.

2.5.2. Fossil-fired generation

We explicitly model the individual fossil-fired units in each region. Through AEMO's Integrated System Plan (ISP) and its predecessor the National Transmission Network Development Plan (NTNDP), data on the production costs of thermal generation units are available.

Generation marginal costs are defined as the sum of fuel and variable operating and maintenance costs for each fossil-fired unit. Fuel costs are calculated as the product of the regional fuel price

[61] For simplicity, we drop price dependencies from Equation (2.2) and all subsequent notation.

[62] For actual demand, we utilize net demand or, equivalently, the difference of demand and dispatched load. Dispatched load tends to occur in NSW and QLD only, and even in these regions it typically represents a small fraction of demand in any given settlement interval. The assumption to ignore dispatched load—or, to consider it as non-price following—is similar to that adopted for must-take generation in Section 2.5.3. Nevertheless, this assumption is conservative as it will tend to understate market power.

[63] When the market is modeled as perfectly competitive, results are relatively insensitive to the elasticity assumption, as price is set at the marginal cost of system production and the range of prices is relatively modest.

and a unit-specific "heat rate," which is a measure of fuel-efficiency. The marginal cost of unit i in region r at time t is, therefore, an affine function:

$$c_{i,r,t} = \frac{VOM_i + FP_{r,t} \cdot HR_i}{LF_{i,y}} \tag{2.3}$$

where VOM_i is the variable operating and maintenance cost per MWh and HR_i is the heat rate for unit i. The regional fuel price for coal, gas, or petroleum, $FP_{r,t}$, is described in greater detail in Section 2.6. Throughout our analysis, we assume that fuel prices are competitively determined. If, however, this is not the case or reported prices exceeded actual prices, then we have underestimated the full impact of market power within the NEM.

The Loss Factor, $LF_{i,y}$, varies by unit i and financial year y and is calculated as the product of the Marginal Loss Factor (MLF) and the Distribution Loss Factor (DLF). As the NEM is a zonal market, these factors represent intra-regional losses. The MLF is an annual projection of the fraction of energy lost when electricity is transmitted between a transmission connection point and the regional reference node (RRN). The RRN is the transmission node where settlement occurs and, by implication, the regional reference price (RRP) is set. If a generator is connected to a distribution network, the DLF represents average projected losses between the generator and the transmission node of the distribution network. Essentially, LF represents the marginal losses for a generator to deliver electricity to the RRN and, thus, allow all generation to be treated uniformly. They are conditional on year since AEMO fixes their values over the Australian financial year starting in July through forward-looking market simulations.

When building regional marginal cost curves, one typically needs to constrain $q_{i,r,t}$ by an expectation of capacity. To do that, electricity benchmark models tend to rely on either Monte Carlo simulation methods (Borenstein, Bushnell and Wolak, 2002) or the expected capacity directly (Bushnell, Mansur and Saravia, 2008; Wolfram, 1999).[64] Here, however, we rely on the self-reported availability of the unit, $\tilde{z}_{i,r,t}$, bid into the market. As such, we adopt the constraint that $q_{i,r,t} \leq \tilde{z}_{i,r,t}$. This inequality recreates the market outcome as accurately as possible and will understate the amount of market power if strategic withholding is being exercised.

[64] Regarding the expectation approach, the capacity of a generating unit is reduced to reflect the probability of a forced outage. The available capacity of generation unit i, is taken to be $(1 - fof_i) \cdot cap_i$, where cap_i is the maximum capacity of the unit and fof_i is the forced outage factor reflecting the probability of an unexpected shutdown.

It is important to note that electricity generation creates additional costs to those considered here. We focus on short-run marginal costs related to fuel and operating expenses. Clearly, sunk costs, including capital and periodic maintenance, should be excluded from any estimate of short-run marginal cost. Various dynamic unit-commitment constraints, such as startup, ramping and run-time costs, are not sunk. And indeed, they are included in observed prices. These constraints create nonconvexities in unit supply functions which present a modeling challenge. Therefore, to assess their impact on observed prices, we construct regional supply curves from actual energy bids. We then find their intersection with a vertical demand curve based on actual regional demand for the specific settlement interval. The resulting simulated prices did not differ significantly from observed ones. As such, we assume dynamic constraints are negligible and our analyses instead rely on observed prices.[65]

2.5.3. Must-take generation

We model hydro, variable renewable energy (VRE), battery storage and non-scheduled generation as must-take. That is, we model this output as non-strategic. We assume the observed output of these units is what would be produced by a price-taking firm in a perfectly competitive market. This implies that the operations of these must-take units does not change. Following Borenstein, Bushnell and Wolak (2002), this assumption biases against finding market power. We discuss the validity of the assumption for the different generation technologies below.

A significant portion of hydro resources within the NEM are owned by hydro-dominant firms, which typically offer cap contracts on futures markets. Such financial products function as insurance for load serving entities against supply scarcity and high spot prices. When spot prices exceed \$300 AUD/MWh, hydro units holding cap contracts must pay the difference to their counterparty. Clearly, they are incentivized to operate when the price is high, so as to avoid absorbing the high prices themselves. This represents a fairly strong incentive to lower wholesale electricity prices and, thus, supports our assumption of price-taking behavior by hydro units.

VRE, including solar and wind, operates as semi-scheduled generation. This implies that, unless directed otherwise, VRE will always produce when it physically can. Non-scheduled generation is

[65] For papers estimating dynamic benchmark models, see e.g. Reynolds (2018) and Jha and Leslie (2021).

similar in that when it is producing, it is automatically accepted during dispatch. Essentially, both VRE and non-scheduled units are must-take generation since they are considered inframarginal to the market.

Batteries operate as scheduled generation. However, given their size, their primary function is shifting current intermittent generation to a future time. As such, they typically bid into the AS instead of the energy market and represent only a small fraction of annual generation in the NEM. In fact, this latter point is applicable across all forms of must-take generation.

2.5.4. Ancillary services

Along with the forms of generation discussed in the previous subsection, we also model some AS as must-take generation. AEMO is obligated to operate the NEM in a secure and reliable manner. This obligation is fulfilled, in part, through Frequency Control Ancillary Services (FCAS), which, as the name suggests, maintain the electrical frequency of the grid.

There are eight markets in the NEM for procuring FCAS, defined by two major categories: regulation and contingency. Regulation frequency control refers to the modification of the supply-demand balance in response to minor deviations in generation or load. Contingency frequency control is the rectification of the supply-demand balance following major contingency events, such as the loss of a generating unit, large industrial load, or transmission element. Regulation services are constantly used to correct for minor changes in the supply-demand balance, while contingency services are only occasionally used but are always enabled to cover unplanned events. The FCAS markets also operate in two directions: raise and lower. The former(latter) is used to correct a minor drop(rise) in frequency, which requires either an increase(a decrease) in generation or a decrease(an increase) in load.

Many generators competing in the energy spot market are also eligible to earn payments for AS, assuming they bid successfully into one of the AS markets. Regulation and contingency, therefore, represent an alternative use for much of the generation capacity throughout the NEM. In the case of the NEM, the provision of energy and AS is not necessarily mutually exclusive. Thus, the set of generators available to ancillary services markets is very similar to that available to the energy market. Since AEMO is procuring extra capacity for the provision of raise AS, these services should be considered as part of market-clearing demand. It is effectively withheld from the spot market and its capacity is otherwise unavailable. For this reason, we add cleared raise AS to demand within each NEM region.[66] We limit the expansion of demand to raise AS, since those generators offering lower AS must already be producing. As such, lower AS cannot be withheld from the spot market. For context, the cleared quantity of raise AS peaked as high as 14% percent of total NEM demand, while its mean percentage was around 7% percent over our time horizon.

2.5.5. Interconnectors

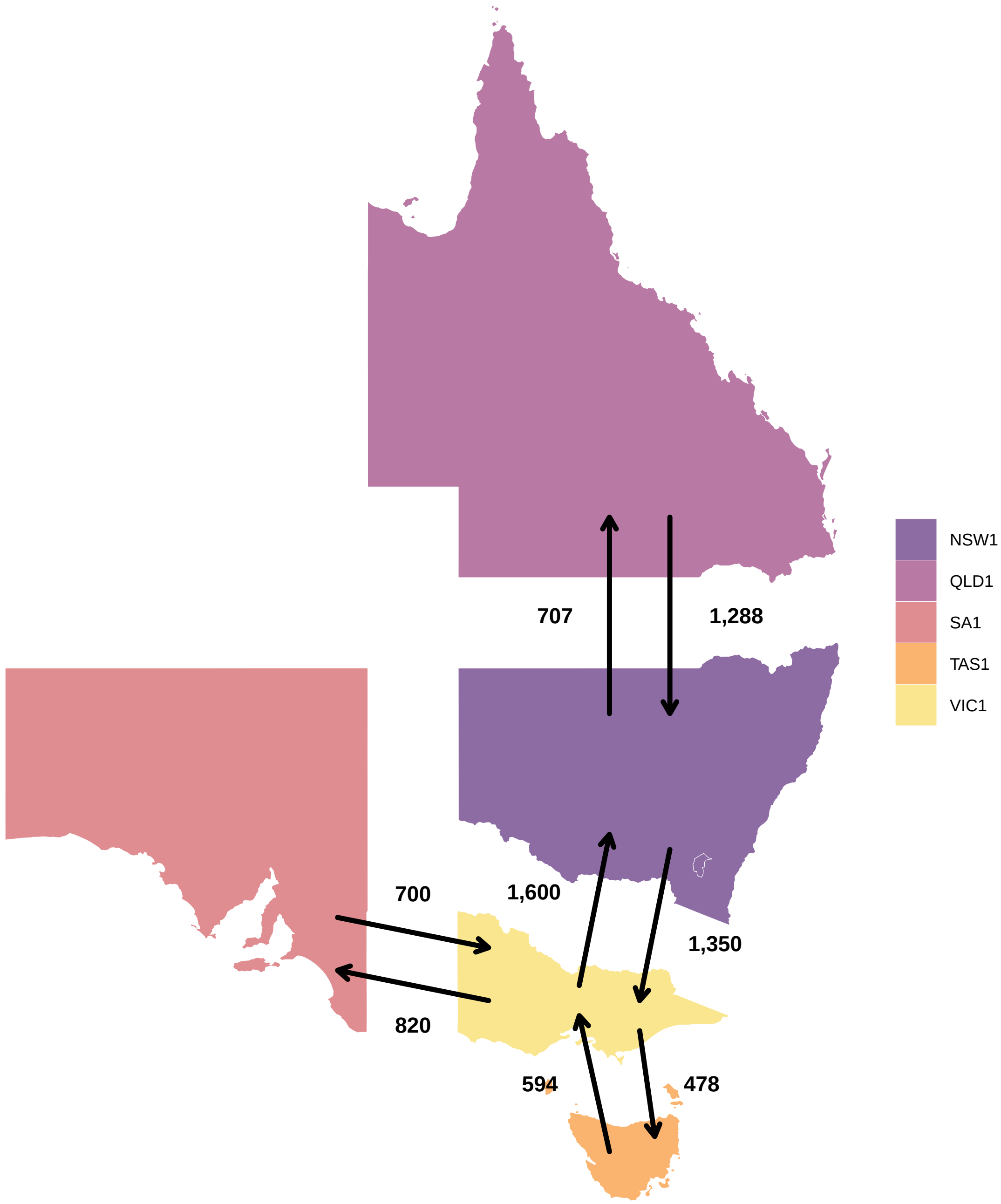
We assume that inter-regional trade is managed to efficiently arbitrage price differences across regions, subject to interconnector limitations. Mathematically, we adopt an approach similar to Metzler, Hobbs and Pang (2005) and Bushnell and Chen (2012) to represent the arbitrage conditions as a set of constraints within the market equilibrium. Essentially, the transmission 'flow' induced by a marginal net injection of electricity in region r can be represented by a power transfer distribution factor (PTDF), $\phi_{r,l}$, which maps injections to flows over interconnectors l. Given that the NEM is a radial model with VIC1 as the hub, a net injection, $y_{r,t} \geq 0$, in region r is assumed to be withdrawn at the hub. In fact, we assume that all net injections balance with their withdrawal in every time period t: $\sum_{r \in R} y_{r,t} = 0$. This condition is subject to the export and import flow limits—$\tilde{T}^{ex}_{l,t}$ and $\tilde{T}^{im}_{l,t}$, respectively—across interconnectors l and time periods t. Figure 2.2 displays the aggregate directional flow limits within the NEM.

2.5.6. Price cost margins

Utilizing the assumptions outlined in the previous subsections, we solve the welfare maximization problem for the perfectly competitive market price for each region and settlement interval within the NEM from 2015 to 2019. Our assumptions regarding must-take generation mean that we directly apply the observed production of hydro, VRE, and AS resources for each settlement period.

[66] Adding raise AS to demand is equivalent to shortening the supply curve by the same quantity.

FIGURE 2.2. NEM maximum aggregated interconnector capacity by direction.



Notes: The map illustrates the maximum inter-regional transmission between NEM regions. The black values next to the arrows represent the maximum flows in MW, which are sourced from AEMO (2017). While these numbers represent upper limits across all time S, our model uses the settlement-specific import and export limits for each region r and settlement interval t. The interconnectors linking each region are: Terranora and QNI traversing NSW and QLD; the eponymous VIC-NSW interconnector; Basslink traversing TAS and VIC; and Heywood and Murraylink traversing VIC and SA.

Once we account for must-take generation and net injections, our competitive benchmark model finds the intersection of the residual demand curve and the marginal cost curve. It estimates the marginal cost for satisfying the residual demand with fossil-fired resources in each settlement interval. This yields an estimated regional marginal cost $c_{r,t}$, which is equivalent to the perfectly competitive regional spot price: $P_{r,t}$.

We rely on RRPs $\tilde{P}_{r,t}$ for the actual market clearing prices. Price-cost margins are then calculated as the difference between the market-realized prices and the perfectly competitive benchmark: $PCM_{r,t} = \tilde{P}_{r,t} - P_{r,t}$.

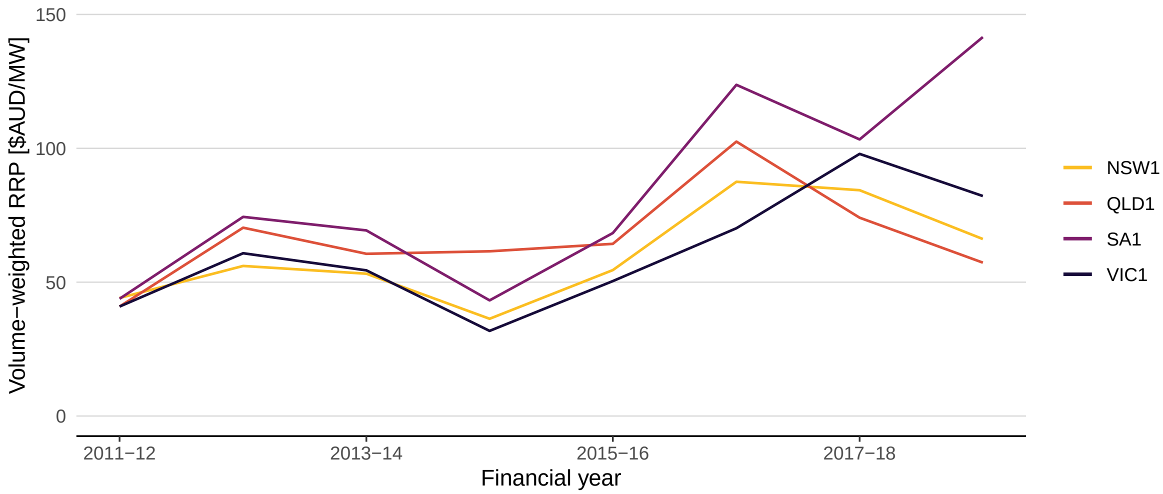
Our procedure produces a some cases in which the price-cost margin is negative.[67] This, of course, does not seem plausible. Absent operational error or predatory pricing, units will not offer power at prices below their true economic short-run marginal costs. That is, actual prices should not be below the simulated perfectly-competitive price. However, the cases of negative margins do not necessarily render our whole approach invalid but rather point to two assumptions influencing the precision of our estimates. First, the non-convexity assumption means that our model ignores dynamic constraints which can lead to cost estimates exceeding observed prices. This happens as startup costs, minimum load constraints, etc., can generate opportunity costs that lower the true marginal costs of operating. Thus, a costly unit may run if it is better off doing so across multiple settlement intervals. Second, the generator cost and fuel data we use is not a perfect representation of actual costs. Given available time and resources, we apply values submitted to and extrapolated from Australian federal regulatory agencies and authoritative public sources. Since the values may not be exact or applicable across our entire sample, our marginal cost estimates may be accurate to a range instead of a point.

2.6. Data

This section provides details regarding the data and its preparation. We utilize detailed hourly market and generation data. These hourly output data are aggregated by region to develop the 'residual demand' in the simulation model. They are also combined with unit-specific cost data to produce regional supply functions for simulations of competitive outcomes.

[67] For QLD, the share of negative price-cost margins is around 7%. For NSW and VIC, it is just above 30%.

FIGURE 2.1. Volume-weighted prices by region and financial year.



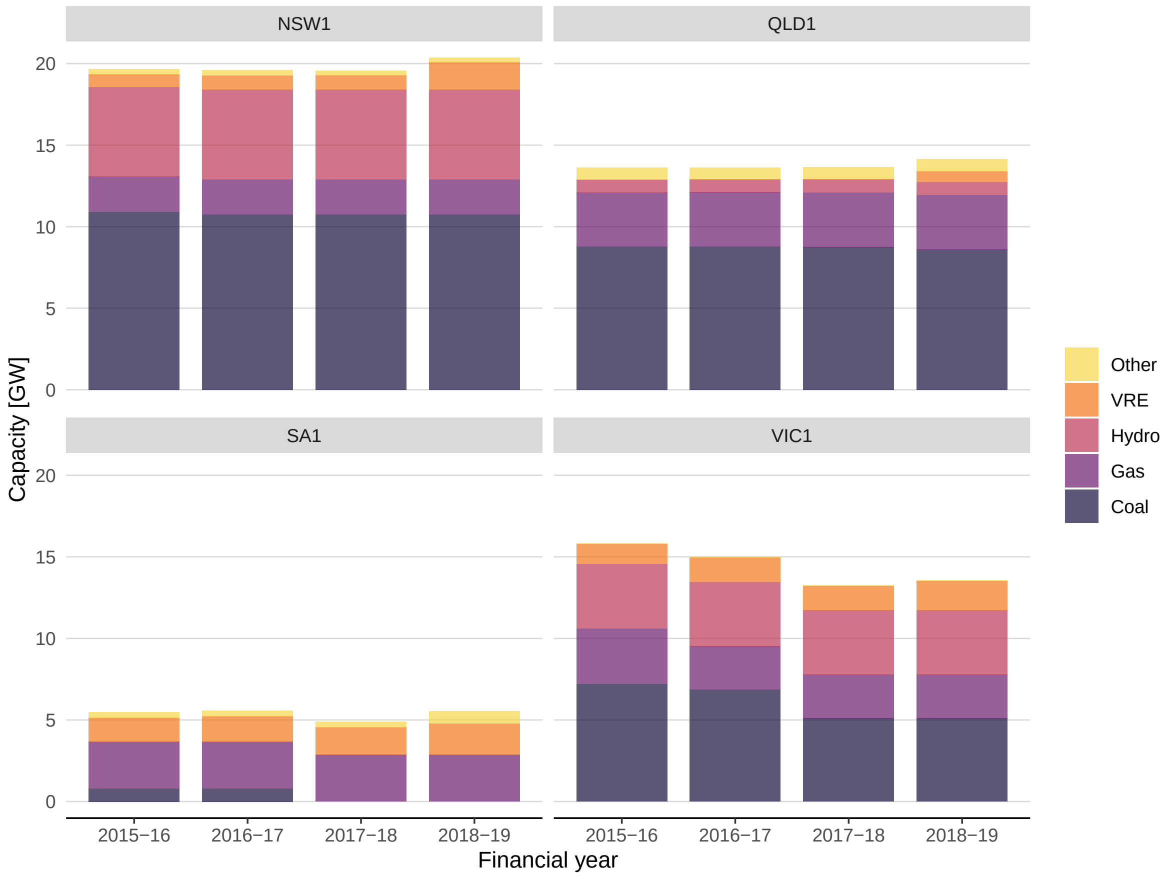
Notes: This plot presents the trends in volume-weighted average prices by region and financial year. Notably, QLD transitions from one of the more expensive regions pre-Direction in 2016-17 to the least expensive in 2017-18 after the QLD Government intervened.

Our primary source for market data is the Market Management System Data Model (MMSDM) published by AEMO. The MMSDM is a centralized, high-frequency and non-annonymized synthesis of publicly available NEM data. It includes a rich set of variables capable of reproducing the various aspects of the NEM at the dispatch-level. For our purposes, we extract the following variables for the period between 2015 and 2019: region-level prices, loads and AS; unit-level availabilities, generation and characteristics; and, interconnector flows.

RRPs serve as a crucial input to our price-cost margin calculations, while actual demand and interconnector flows are exogenous inputs to the welfare maximization problem. Figure 2.1 presents the trends in RRPs across regions and financial years during our sample. Unit-level generation and characteristics allow us to identify and aggregate the various must-take generation sources. As described in Section 2.5, these include hydro, solar, wind, batteries, non-scheduled generation and raise AS. Figure 2.2 provides an overview of generation capacity by region and technology, while Figure 2.C.2 in Appendix 2.C provides the equivalent for total generation.

The data flowing into calculations of our unit-specific, time-dependent marginal costs are sourced more broadly. To begin, we extract fossil-fired unit availabilities and marginal loss factors from the MMSDM. To classify units, we gather fuel types and descriptions from the “Registration

Figure 2.2. Capacity by region, technology and financial year.



Notes: This plot presents generation capacity by region and technology between the 2015-16 and 2018-19 financial years. The capacities for each bar are based on a snapshot taken on the first day of the new financial year, 1 July. Variable renewable energy (VRE) includes large-scale solar and on-shore wind. Other includes liquid fuels and biomass. We do not account for the regional interconnector capacities, nor for roof-top solar installations which are significant in Australia. An equivalent plot presenting total generation by region, technology and financial year is presented in Figure 2.C.2 in Appendix 2.C.

and Exemptions List" published by AEMO. The List represents a cross-section of all registered participants in the NEM at a given time. It is updated upon changes in status and includes information about generator characteristics, capacities, and ancillary services.

We take heat rates and VO&M expenditures per unit of electrical energy from the ISP and NTNDP reports and synthesized within the "Fuel & Technology Cost Review." The NTNDP and ISP are simulation exercises developed by AEMO to provide guidance on the efficient development of the NEM. The parameters used for their simulations are gathered from a industry survey and serve as essential inputs for our model.

Finally, we collect fuel prices from a diverse set of sources dependent on the specific fuel. For natural gas, we rely on spot markets managed by AEMO, namely: the Declared Wholesale Gas Market (DWGM) in VIC and the Short Term Trading Market (STTM) in NSW, QLD and SA. The latter trades daily, while the former trades intra-day. TAS does not currently host a spot market; however, it is connected to the DWGM in VIC through the Tasmanian Gas pipeline. Thus, we apply a markup for transmission under the Bass Strait to all TAS natural gas units. We also apply a haulage change to all mainland units. These are unit-specific based on the relevant pipeline connections. The dataset was developed for the sole purpose of our model by associating all natural gas units with nearby gas transmission infrastructure. The applicable tariffs were manually collected from the various pipeline owners based on online information.

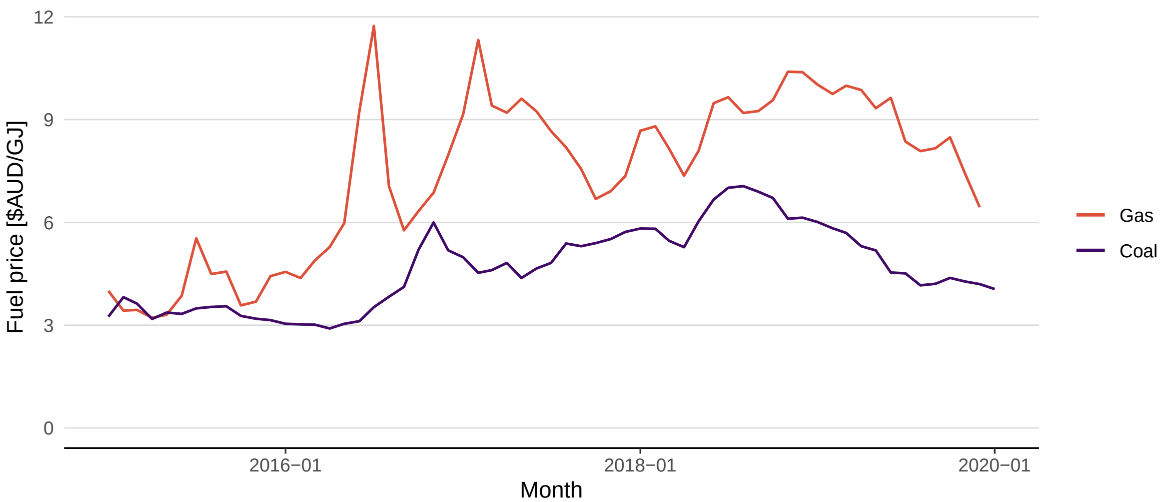
For coal, the model requires price timeseries for the type of coal regionally available. NSW and QLD rely predominantly on black coal, while brown coal dominates in VIC and SA. TAS does not have any coal units. For black coal, we use on daily spot prices of Newcastle thermal coal published by Bloomberg.[68] For brown coal, there is a dearth of public pricing data. This is a consequence of most brown coal generators being located at the mine mouth and engineered for the specific coal quality and composition. Typically, the mine and power plant are vertically integrated or they strike confidential, bilateral supply contract. Either option obviates the need to procure fuel from the open market. Thus, we extrapolate brown coal prices from the Newcastle spot data and the ratio of brown-to-black prices in the ISP from the "Coal and Biomass price".

For petroleum products, we require price timeseries for diesel and kerosene. The Australian Institute of Petroleum (AIP) provides daily diesel terminal gate prices (TGP) within each Australian capital city. Unfortunately, to our knowledge, kerosene price data are not publicly available for Australia. Since its kerosene is mostly sourced through Singaporean markets, we determine the spread between kerosene and diesel spot prices in Asia and add it to the state-based diesel prices from the AIP.[69] Justification for this methodology relies on the fact that the cost components for

[68] Specifically, we procure "Australia Newcastle Port Thermal Coal 6000 kcal/kg FOB Spot Price" data under the ticker "COASNE60."

[69] The data are sourced from Bloomberg: "Asia Gasoil 10ppm FOB Singapore Cargo Spot" for diesel under the ticker "GASL500P" and "Singapore Jet Kerosene Spot Price" for kerosene under the ticker "JETKSPOT."

FIGURE 2.3. Daily fuel prices averaged by month.



Notes: This plot presents the trends in coal and gas prices ($AUD/GJ) across Australia by month between 2015 and 2019. Coal is sourced from the daily Newcastle Port Thermal Coal 6000 series from Bloomberg. Gas is an average of daily spot prices from the DWGM and STTM provided by AEMO. At the start of 2016, both input fuels increase in price, though gas climbs higher and remains above coal for the remainder of our sample.

kerosene and diesel are equivalent except for their Singaporean spot prices. That is, the Australian excise rates for both fuels are equivalent, implying that the difference in spread is solely due to the difference between their respective spot prices.[70]

As heat rates are provided in GJ/MWh, we convert all prices to GJ using regional energy content values from the "Guide to the Australian Energy Statistics" published by the Department of the Environment and Energy (DEE). Since natural gas is already priced per GJ, this only applies to the coal and petroleum products. Figure 2.3 provides the timeseries for the cleaned daily fuel prices in $AUD/GJ.

It should be noted that all unit-specific datasets are merged on unit ids and, in some cases, names. Unfortunately, the merge is incomplete and some units lack necessary variables. Thus, using data available from generators with similar technology and geographic proximity, we extrapolate any missing values. While this process introduces some uncertainty, it ensures we have complete supply curves and cost information is consistent across all units. Additional information regarding

[70] The methodology of transforming regional Australian diesel prices to kerosene prices was developed by combining resources from the AIP, Australian Tax Office (ATO) and the Australian Competition & Consumer Commission (ACCC). Additional information is available on request.

assumptions and extrapolations is available upon request. Table 2.B.1 in Appendix 2.B summarizes the data sources by providing a mapping to the model variables.

2.7. Results

Using the model described above, we simulate the perfectly competitive market outcome for each settlement interval from 2015 to 2019 inclusive. Below, we present a comparison of actual versus simulated market results germane to the "Stanwell Direction" which occurred on 6 June 2017. We primarily discuss its effects on price-cost margins and exports within QLD.

2.7.1. Price-cost margins

During the 2016-17 financial year, average spot prices increased dramatically across the NEM. Most regions experienced record annual average prices, nearly double levels from only two years prior (AER, 2018*b*). While prices eased in most regions during the subsequent years, they stubbornly remained above pre-2016-17 annual averages (AER, 2020).

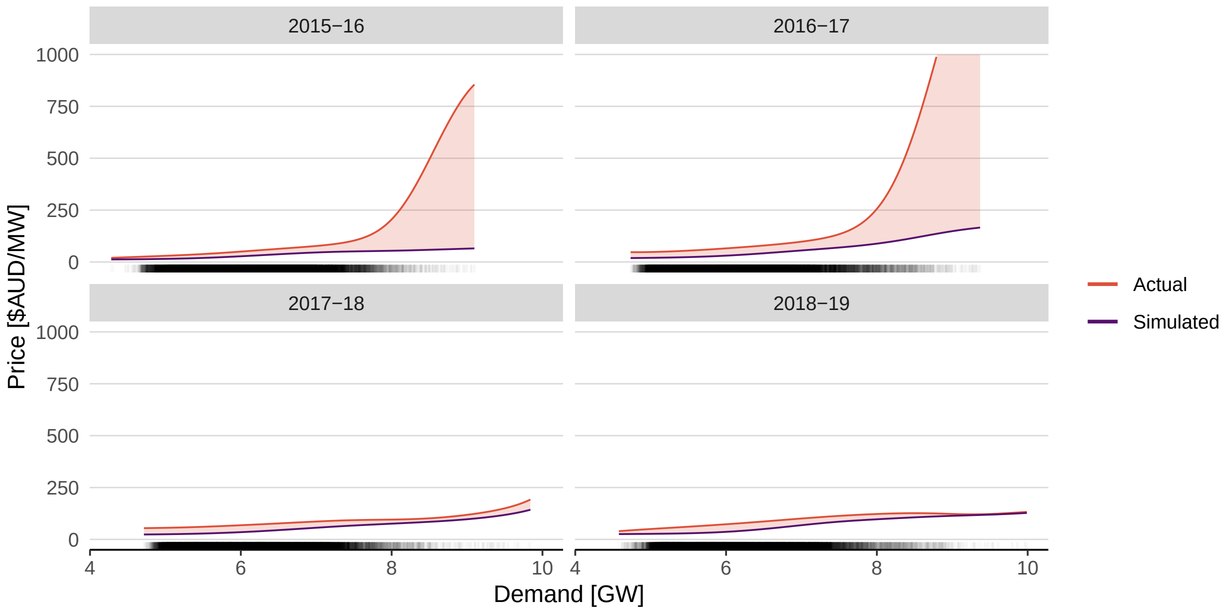
Market policymakers and regulators identified several drivers of the NEM-wide price surge. In VIC, price pressure increased after the closure of Hazelwood Power Station (HPS) in March 2017 (AER, 2018*a*). Hazelwood was a large brown coal generator representing around five percent of the NEM's capacity. Its decommissioning followed years of similar closures and stagnant investment in dispatchable generation across the NEM. These conditions resulted in a much tighter supply-demand balance, where low-cost coal was initially replaced by more expensive gas and hydro generation. The regulators also observed that black coal generators in NSW and QLD simultaneously increased their offer prices. In part, this was understood to be a consequence of increasing coal costs and supply interruptions. However, the regulators also believed that surging gas prices across the Eastern seaboard decreased competitive pressure on baseload plants. As a result of that decrease, some black coal generators periodically engaged in shadow bidding up to the marginal costs of the next highest generator in the merit order, typically gas plants. In fact, the AER found average offers from NSW and QLD black coal generators increased more than underlying costs (ACCC, 2018; AER, 2017*c*).

Prices relented in QLD and NSW starting in 2017-18, though they remained above pre-HPS-closure averages. Market intervention by the QLD Government—including the Stanwell Direction in June 2017—was cited as a major contributor towards decreased price pressures. Figure 2.1 supports this narrative through the results of our price-cost analysis. It displays non-parametric means of actual versus simulated prices by region and financial year. Actual prices are based on RRPs from AEMO, while simulated prices are generated using our model of perfect competition and represent the market's marginal cost. The shaded area between the two prices curves represents the average price-cost margin for the particular level of regional demand. Panel (a) presents the results for QLD, where the two years following the Direction clearly break from the pattern of the two years prior to it. During the preceding years, 2015-16 and 2016-17, actual prices exceed simulated ones only modestly at low and intermediate levels of demand; however, at high levels, the average price-cost margin explodes. At low levels, the price gap is anywhere between \$10 to \$30 AUD, while at high levels, it can increase by hundreds and even thousands of AUD. Post-Direction, the large price-cost margins at high levels of demand evaporate and, instead, mirror those at lower levels of demand. Thus, there is strong indication that the Direction played a role in reducing excessive margins at high levels of demand within QLD.

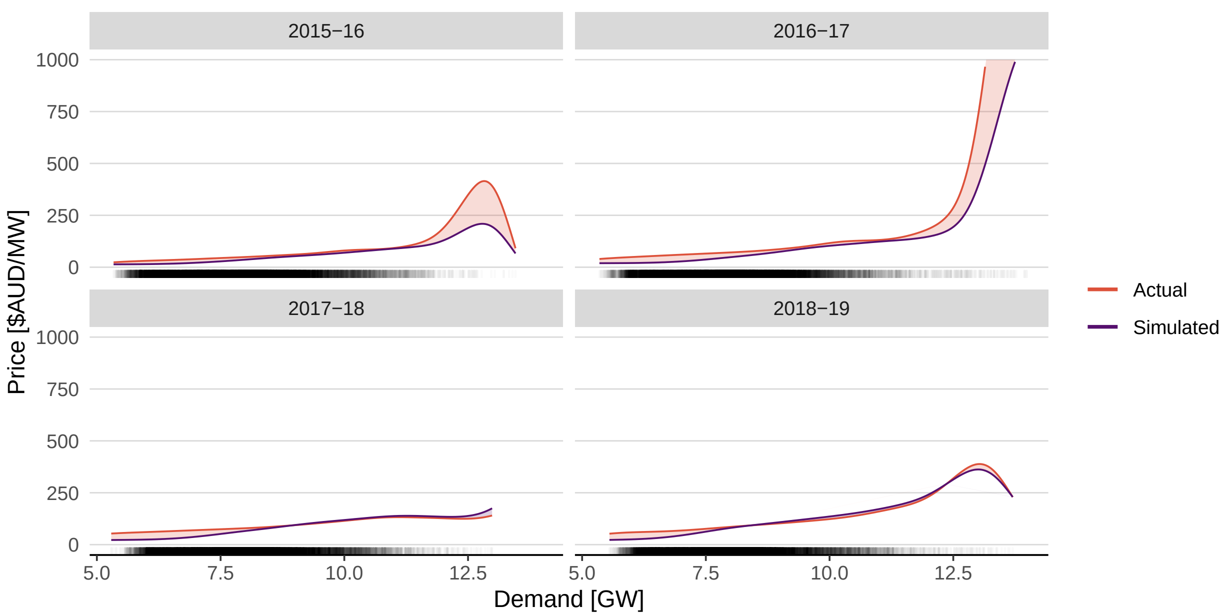
Panel (b) presents results for NSW, which are similar but less dramatic to those from QLD. The pre- and post-Direction pattern repeats, as large margins at high levels of demand disappear in the post-period. Panel (c) presents results for VIC, where the pattern does not repeat. This difference in outcomes between NSW and VIC can perhaps be best explained by their respective proximity to QLD. Whereas NSW is a neighbor and directly imports and exports power from QLD, VIC is two degrees removed and is only indirectly affected by changes in QLD. In essence, any effect from the Stanwell Direction in VIC is likely overwhelmed by local conditions.[71]

[71] In particular, the Basslink interconnector between VIC and TAS was inoperable for six months during 2015-16. This outage overlapped with high summer temperatures pushing prices up as more expensive mainland gas resources were forced to make up the difference (AER, 2017*d*). The 2016-17 financial year saw the return of the Basslink interconnector as well as one of the mildest summers in recent times resulting in few price spikes (AER, 2018*b*). Extreme temperatures, however, returned during the summers of 2017-18 and 2018-19 and led to high demand periods. These coincided with generator outages, exacerbating the local supply-demand balance which was already strained as a consequence of the Hazelwood closure in early 2017 (AER, 2020). As such, the VIC plots in Figure 2.1 better reflect its local market conditions with high prices absent during 2016-17 and featuring prominently during the other three financial years.

Figure 2.1. Price-cost margins by region and financial year.



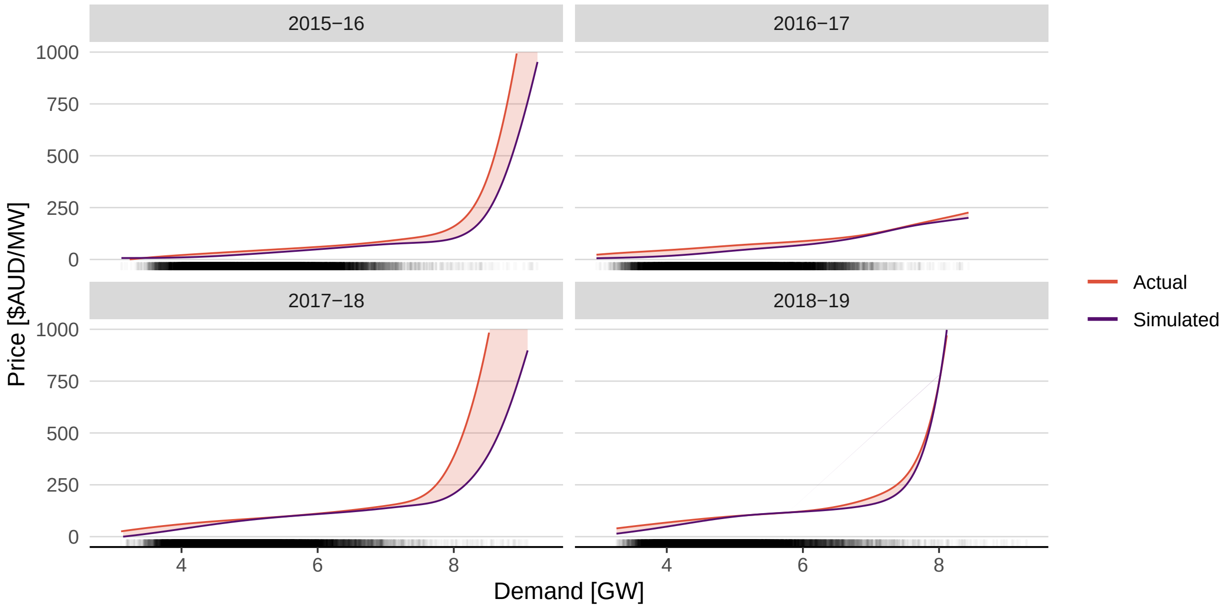
(a) QLD.



(b) NSW.

Notes: See below.

Figure 2.1. Price-cost margins by region and financial year (cont).



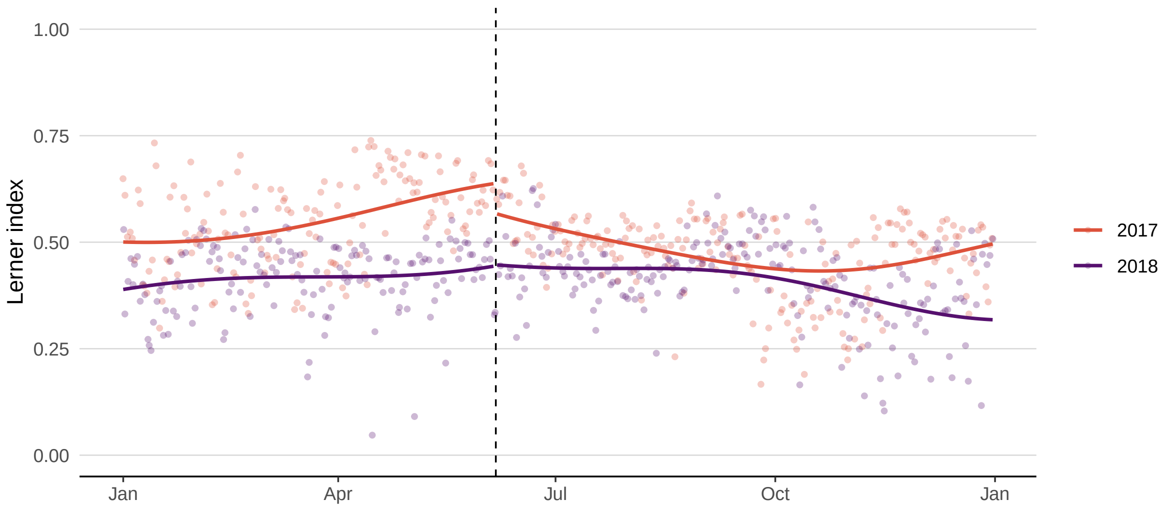
(c) VIC.

Notes: This plot presents non-parametric means of actual versus simulated prices by region and financial year. The shaded area between the two prices curves represents the average price-cost margin for the particular level of regional demand. Actual prices are based on RRPs from AEMO, while simulated prices are generated using a multistate model with endogenous transmission flows. The price curves are local polynomial regressions using a normal kernel with a 500 MW bandwidth. The black lines along the horizontal axis provide the density of actual demand. The shown range is limited to between 0 and $1,000 AUD/MW, while the full range can be viewed in Figure 2.C.3 located in Appendix 2.C.

Figure 2.2 reinforces the evidence for the step change in margins that occurred in QLD post-Direction. The Figure overlays daily average Lerner index values during the 2017 and 2018 calendar years for QLD.[72] The vertical dashed line identifies the date of the Direction, while the curves represent the result of local polynomial regressions. The plot serves to highlight that relative markups decreased after the Direction in 2017, contrasting with their stability during the subsequent year. Figure 2.C.4 in Appendix 2.C provides the companion plots for NSW and VIC. The former displays a similar drop in average Lerner index values post-Direction, while the latter does not. It is possible that the pattern of Lerner index values across these three plots is a consequence of

[72] The Lerner index is the ratio of the price-cost margin over actual prices and is a standard measure of market power.

FIGURE 2.2. Daily average Lerner index values for QLD by calendar year.



Notes: This plot presents daily average Lerner index values for QLD during the 2017 and 2018 calendar years. Lerner index values are based on actual market outcomes from AEMO and simulated runs from a multistate model with endogenous transmission flows. The vertical dashed line identifies the date of the QLD Government's "Stanwell Direction" which occurred on 6 June 2017. The curves are local polynomial regressions using a normal kernel with a 45 day bandwidth. They serve to highlight that relative markups decreased after the Direction in 2017, which contrasts with their stability during the subsequent year. Similar plots for NSW and VIC are provided in Appendix 2.C.

measurement error. However, there is no reason to believe that these errors commence concurrently with the Direction.

In order to better understand the changes in Lerner index across time, we must account for differences in the relative levels of demand over these periods. As described above, we would expect estimated market power to decrease post-Direction at high demand levels. Figure 2.3 shows kernel regressions of the Lerner index on regional demand for the four financial years of interest. The dashed curves represent the outcomes for the pre-Direction period, while the solid curves shows the post-period developments. Panels (a) and (b) present the results for QLD and NSW, respectively. As anticipated, there is a sharp drop in the Lerner index—and thus, in market power—at high levels of demand in both regions post-Direction. They differ, however, at lower levels of demand. NSW experienced a decrease post-Direction across almost all levels; whereas, QLD only experienced a decrease at high levels. This is consequential for the impacts of the Direction, which we will return to below. Panel (c) presents the results for VIC, which diverge significantly from the other two regions. This is particularly true for high-levels of demand where there is no discernible pattern in relation to the Direction.[73]

Having generated estimates of price-cost margins for each settlement interval over our five-year sample period, we can examine in more detail some additional measures to gain insight into the underlying dynamics of the market. In particular, the difference in profits between actual and simulated outcomes can be used as a measurement of market power rents and, thus, help understand the effects of the Direction. We calculate total profits in a given settlement interval by summing over the set of strategic, fossil-fired units in the model, where profits for each individual unit are the product of their generation and the difference between the market price and their marginal cost. In our model notation, this can be represented for unit i in region r during interval t as:

$$\pi_{i,r,t}(q_{i,r,t}) = [P_{r,t} - C_{i,r,t}(q_{i,r,t})] \cdot q_{i,r,t} \tag{2.4}$$

which defines simulated profits. Actual profits, $\tilde{\pi}_{i,r,t}$, are calculated symmetrically with market prices replaced by $\tilde{P}_{r,t}$ and unit quantities with $\tilde{q}_{i,r,t}$. Unit profits are then summed over all units within a region r and over a set period of time T. The difference in actual versus simulated summations results in an estimate of market power rents:

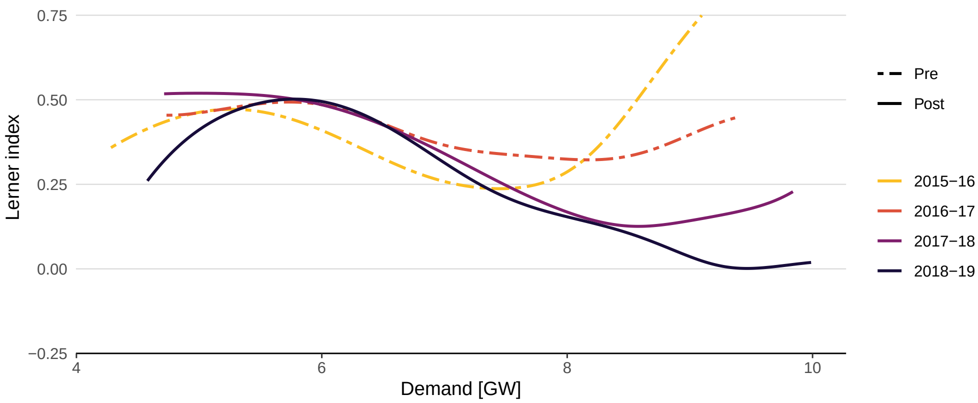
$$\Delta\pi_r = \sum_{t\in S}\sum_{i\in r}\pi_{i,r,t}^{actual} - \sum_{t\in S}\sum_{i\in r}\pi_{i,r,t}^{simulated} \tag{2.5}$$

where the dependent variables have been dropped for convenience.

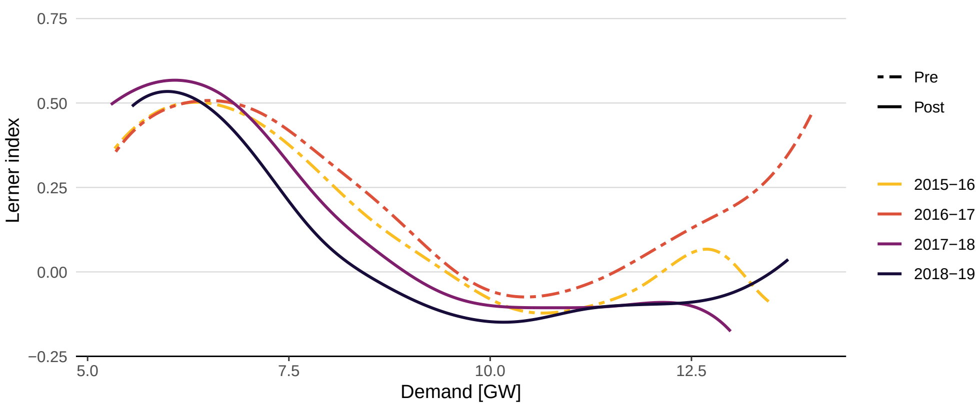
Table 2.1 reports financial year market power rents along with actual versus simulated mean generation, prices and profits. The common outcome across NSW, QLD and VIC is that market power rents surged during the 2016-17 period just prior to the Direction: we estimate they exceed two billion AUD within NSW and VIC and approach six billion AUD within QLD. These estimates represent a little under half of the actual profits for these three regions during the 2016–17 financial year, so they are significant numbers. After the Direction, subsequent financial years experienced a sizable decrease in rents.

[73] At low levels of demand, VIC experienced a large decrease in market power which far exceeded changes in either NSW or QLD. After Hazelwood shuttered, supply-demand conditions in VIC were quite tight. As a result, the frequency with which the remaining in-region brown coal generation was marginal decreased significantly (AER, 2018*a*). As a result, more expensive forms of generation replaced brown coal as the marginal generator, thus narrowing the Lerner index and reducing market power in VIC.

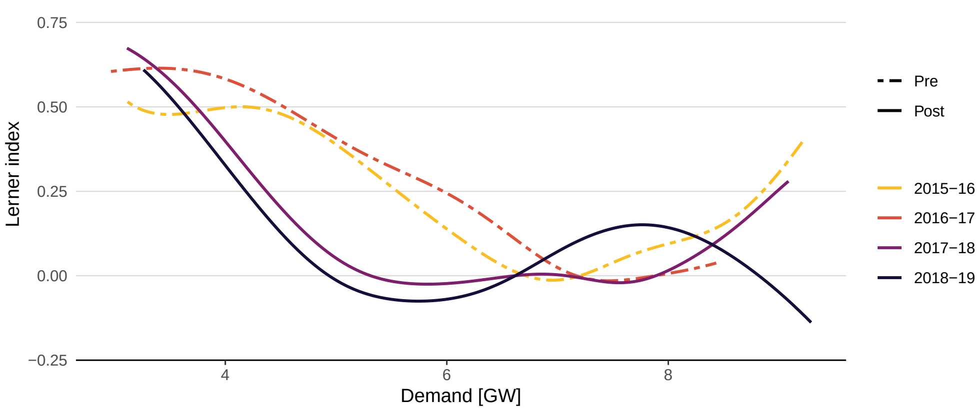
FIGURE 2.3. Lerner index densities by region and financial year.



(a) QLD.



(b) NSW.



(c) VIC.

Notes: This plot presents non-parametric means of the Lerner index versus actual demand by region and financial year. Lerner index values are based on actual market outcomes from AEMO and simulated runs from a multi-state model with endogenous transmission flows. The dashed curves occurred in years prior to the QLD Government's "Stanwell Direction," while the solid curves occurred afterwards. The curves are local polynomial regressions using a normal kernel with a 500 MW bandwidth.

Table 2.1. Actual price, simulated marginal cost and difference in profits by financial year

FY	*Actual*			*Simulation*			
	Generation [MW]	**Price** [$AUD/MW]	**Profit** [$billion AUD]	**Generation** [MW]	**Price** [$AUD/MW]	**Profit** [$billion AUD]	**ΔProfit** [$billion AUD]
Panel A: NSW							
2015-16	6,748	51.6	4.60	7,725	38.3	3.51	1.09
2016-17	6,701	80.6	7.79	7,993	55.6	5.62	2.17
2017-18	6,785	81.9	7.27	7,929	66.4	6.28	0.99
2018-19	6,776	88.1	8.06	7,661	79.5	7.67	0.39
Panel B: QLD							
2015-16	6,454	60.0	4.88	6,029	31.1	2.01	2.87
2016-17	6,645	92.7	8.45	6,082	40.3	2.61	5.85
2017-18	6,786	72.4	5.36	6,260	40.8	2.18	3.18
2018-19	6,454	80.0	5.87	6,082	47.0	2.71	3.17
Panel C: VIC							
2015-16	5,404	46.2	3.53	5,332	31.7	2.22	1.31
2016-17	5,183	66.6	4.83	4,870	42.6	2.78	2.05
2017-18	4,462	90.8	6.09	4,482	78.8	5.18	0.91
2018-19	4,235	107.9	7.22	4,252	99.9	6.69	0.53

Notes: This table presents the difference between actual and simulated profits. For each generator and settlement interval, profits are calculated as the product of unit generation and the difference between price and marginal cost. These are then summed over all units and intervals to arrive at an estimate for the financial year, actual and simulated profits and their difference. Monthly results are provided in Table 2.C.1 in the Appendix.

Notably, QLD's rents remained in excess of three billion AUD in both 2017-18 and 2018-19. In fact, this is above those estimated for the 2015-16 financial year when the Direction did not yet exist. Given these results and the Lerner index densities in Figure 2.3a, the Direction appears to have mitigated the most egregious abuses of market power by QLD generators. These represent the exercise of market power at high levels of demand, when its use would reap the greatest return. However, Figure 2.3a also shows that the Direction had little effect on markups at lower levels of demand. Significantly, generators continued to exercise market power and earn profits in excess of competitive rents in QLD during the post-Direction period.[74]

[74] Appendix 2.C contains a number of companion plots and tables which provide similar conclusions to Table 2.1. Table 2.C.1 presents identical data but at the monthly level. Figures 2.C.5 and 2.C.10 present daily average Lerner

2.7.2. Exports

We now turn to the question how the exercise of market power in QLD may have impacted other regions, in particular NSW. In the previous subsection, we established that the bidding behavior in QLD at high demand levels changed post-Direction; nevertheless, generator revenues remained relatively stable.[75] As QLD generators derive revenue from both satisfying local load as well as exporting power to neighboring regions, this leaves open the question of whether the change in generator bidding behavior in QLD had a symmetric effect on the electricity costs across QLD and NSW consumers. The following analysis attempts to answer this question, by first assessing the Direction's impact on exports and prices, before returning to revenue effects.

Figure 2.4 displays the actual versus simulated average QLD exports between 2015 and 2019. Pre-Direction, both sets of exports were in the vicinity of 200 to 600 MW on average. Post-Direction, they diverged strongly: actual exports increased and were typically above 500 MW, while simulated exports decreased and were typically below 250 MW.[76] Broadly, exports increased after the Direction; whereas, our perfectly competitive benchmark predicted a decrease for that time period given the market fundamentals.

Across interconnectors, electricity tends to flow from less expensive to more expensive regions. Generators from exporting regions are compensated at the importing region price.[77] Figure 2.5 presents actual versus simulated prices in QLD and NSW by financial year. As can be seen in

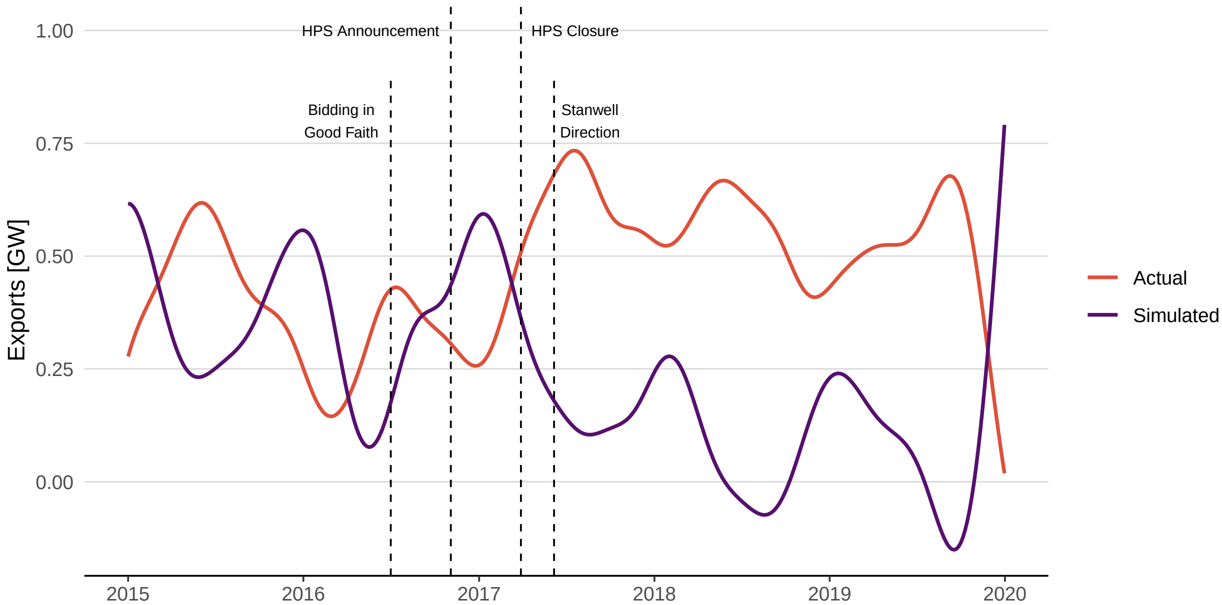
index and monthly total revenues by region between 2015 and 2019, respectively. The demonstrate that QLD margins and revenues decrease post-Direction, but yet remain significant.

[75] See, among others, Figure 2.C.6.

[76] An interesting feature of Figure 2.4 is that the curves appear to be negatively correlated. Figures 2.C.7 and 2.C.8 in Appendix 2.C attempt to shed some light on this relationship. Figure 2.C.7 plots QLD export densities versus QLD actual demand. The mean curve for actual outcomes is negatively related—that is, as demand increases, exports decrease. This is typical, as one would expect increasing local demand to be met by either local supply or relatively less expensive imports. The simulated curve, on the other hand, displays a "U"-shaped relationship. This implies that, in a perfectly competitive market, QLD would export more at both low and high levels of demand. The reason for this can be found in Figure 2.C.8, which plots normalized demand in the other NEM regions against QLD demand. In contrast with the other three regions, NSW is positively correlated with QLD demand over its entire range. In essence, QLD and NSW are good predictors for one another: when demand peaks in QLD, it is likely high in NSW too. Since the supply-demand balance is tighter in NSW compared to QLD, NSW moves up its merit order more rapidly. Thus, in our simulation of perfect competition, QLD tends to export power to NSW at high levels of demand. This explains why the curves in Figure 2.4 tend to move in opposite directions.

[77] In fact, this is a simplification of how revenues from inter-regional trade are allocated within the NEM. Strictly speaking, all generators are compensated for their output at their RRP. Only those who have purchased capacity rights along an interconnector have a claim on the respective transmission revenues, which are equal to the product of the inter-regional price difference and interconnector flows. Our simplification is equivalent when considering the aggregate revenue across all generators in an exporting region.

FIGURE 2.4. Average exports from QLD by dispatch interval between 2015 and 2019.

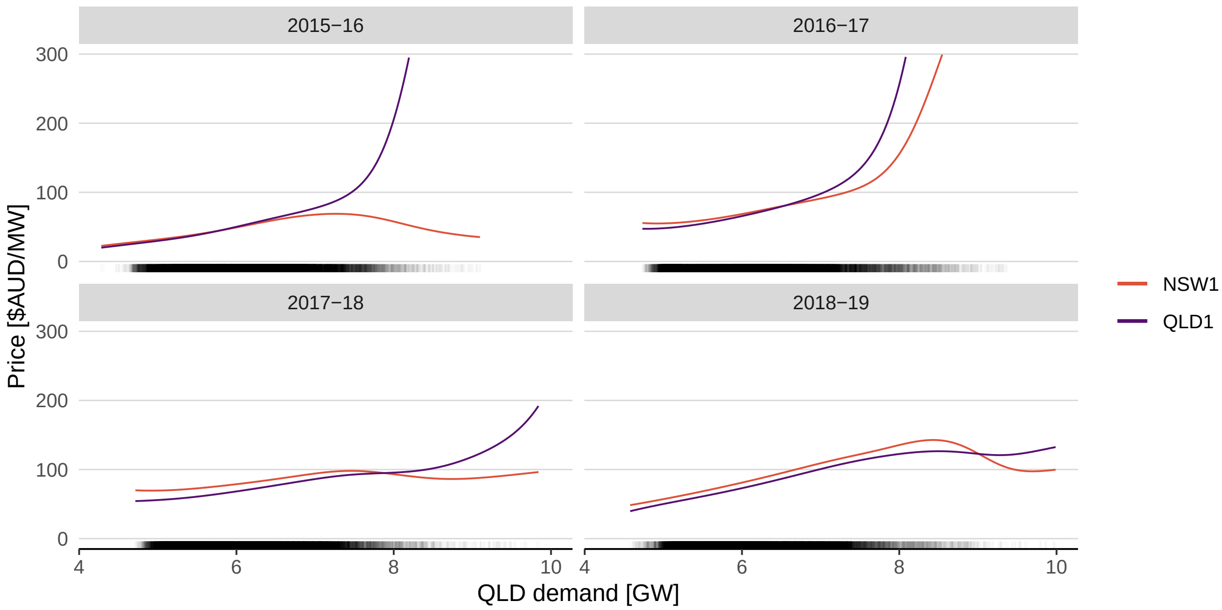


Notes: This plot presents actual versus simulated exports from QLD by dispatch interval between 2015 and 2019. Actual exports are based on market outcomes from AEMO, while simulated exports are generated using a multistate model with endogenous transmission flows. The vertical dashed lines identify major events in the leadup to the QLD Government's "Stanwell Direction" which occurred on 6 June 2017. The curves represent local polynomial regressions using a normal kernel with a 45 day bandwidth.

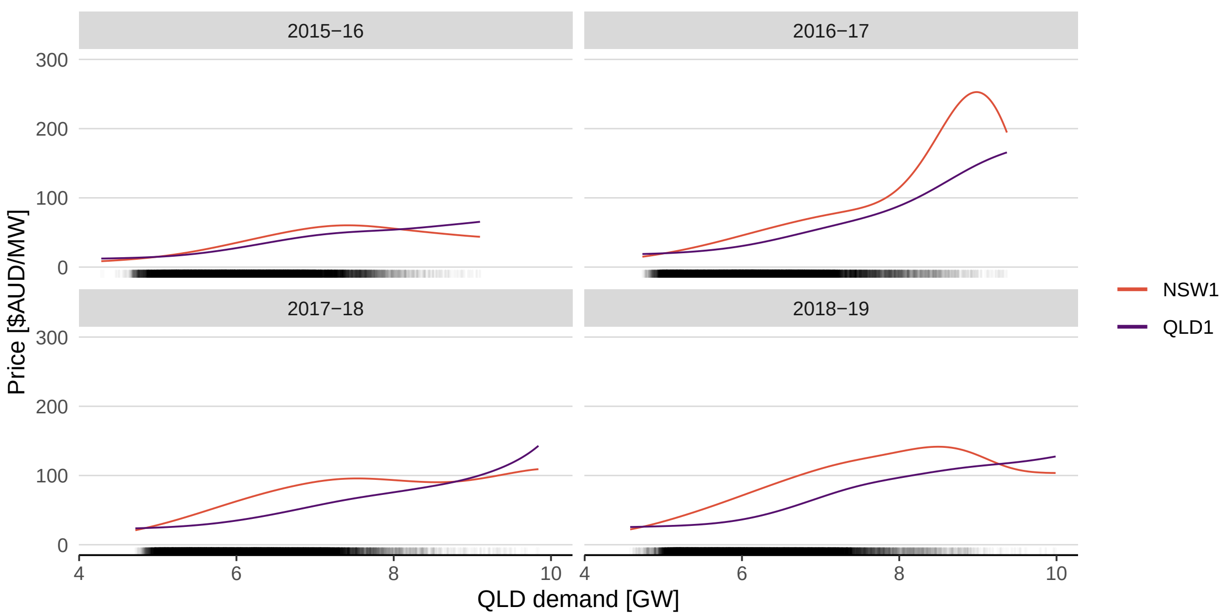
Panel (a) which illustrates the actual market outcomes, QLD had a positive price differential with NSW pre-Direction. Thus, prices in QLD were on average greater than those in NSW, leading to lower exports out of QLD. Post-Direction, this relationship flips for the majority of of QLD demand levels. This leads to higher exports and corresponds to the trends observed in Figure 2.4.

In Panel (b) which shows simulated outcomes for our perfectly competitive benchmark, QLD has a negative price differential across most demand levels and all financial years. As such, they would be expected to export to NSW the majority of the time. For our analysis, the important observation is that a significant price gap emerges post-Direction. This contrasts with the actual outcomes, where QLD prices decrease below those in NSW, but the gap between them remains relatively small. This means that, though simulated exports from QLD decreased, the marginal revenue earned on each additional MW is greater than in the actual market.

Figure 2.5. Actual vs simulated price densities by region and financial year.



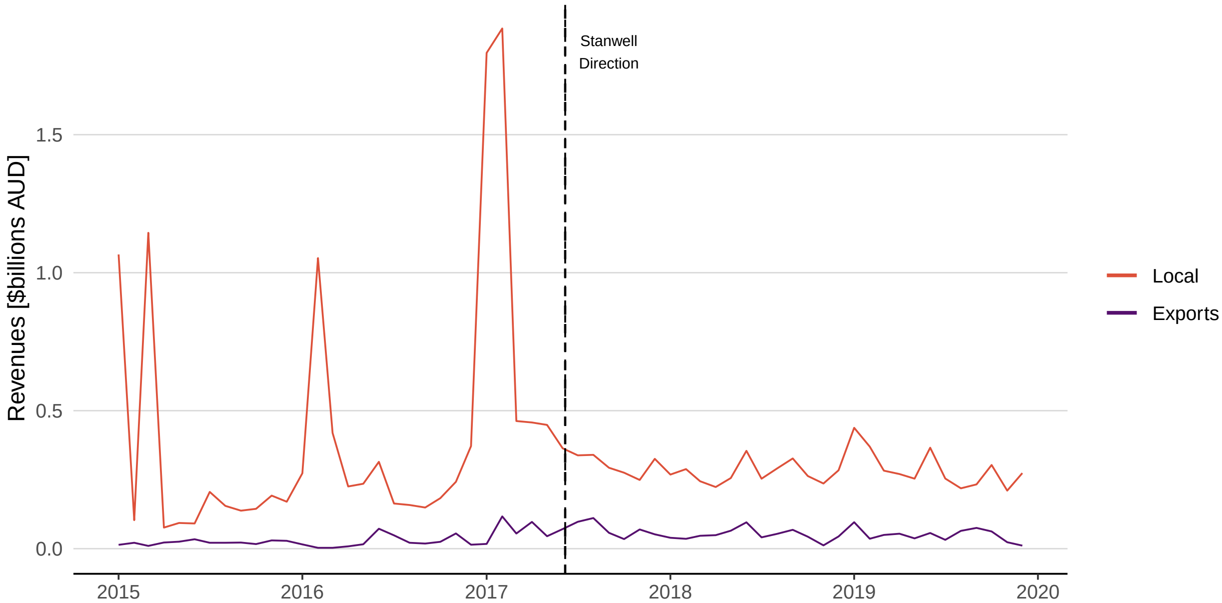
(a) Actual.



(b) Simulated.

Notes: This plot presents non-parametric means of actual versus simulated prices in QLD and NSW by financial year. Actual prices are based on RRPs from AEMO, while simulated prices are generated using a multistate model with endogenous transmission flows. The price curves are local polynomial regressions using a normal kernel with a 500 MW bandwidth. The black lines along the horizontal axis provide the density of actual QLD demand. The shown range is limited to between 0 and $300 AUD/MW.

Figure 2.6. Monthly revenue differences in QLD from local and export demand between 2015 and 2019.



Notes: This plot presents the monthly difference between actual and simulated revenues in QLD from local versus export demand between 2015 and 2019. Actual revenues are based on market prices and quantities from AEMO, while simulated revenues are generated using a multi-state model with endogenous transmission flows. The dashed vertical line represents the QLD Government's "Stanwell Direction" which occurred on 6 June 2017.

Therefore, in the actual market, prices decrease and exports increase, while the opposite occurs in our perfectly competitive benchmark. The result is that these effects essentially cancel each other out. Figure 2.6 displays monthly revenue differences for QLD from both local and export sources. We define 'revenue difference' as the difference between actual and simulated revenues in any given month. As can be seen, export revenues remain relatively stable throughout our sample. Moreover, they mirror local revenue differences in the post-Direction period. As such, we can conclude that the Direction affects QLD and NSW customers symmetrically.

2.8. Concluding remarks

In this paper, we study the intertwined effects of public ownership and market power in the context of the 2017 "Stanwell Direction"—a formal instruction made by the QLD Government to a government-owned generator demanding it put downward pressure on wholesale electricity prices.

The Direction was credited with lowering prices almost immediately; however, its effects on market power and margins within the state were less obvious.

To investigate these effects, we first review the history of government ownership within the QLD electricity sector and, in particular, its relationship to generation market structure and concentration. We then build a competitive benchmark model, and, relying on various data, including high-resolution electricity market data from AEMO, we produce a counterfactual competitive time-series. Comparison of actual market outcomes with our benchmark simulations suggests that abuses of market power by QLD generators during periods of high demand decreased after the release of the Direction. However, we find no evidence for the Direction affecting markups at lower levels of demand. In fact, the analysis indicates that generators continued to exercise market power and earn profits in excess of competitive rents in QLD during the post-Direction period. This represents a continuation of the pattern of market power exploitation that existed prior to the Direction. We also find that the Direction's effects were symmetric for both QLD and NSW customers.

These findings open broader questions on the efficiency of government ownership in the QLD generation sector. In their seminal work on privatization, Sappington and Stiglitz (1987) argue that operating a government-owned company is only justified when the welfare loss of the market failure exceeds the costs of government failure. In such circumstances, government-owned companies are best suited when: (1) there already exists a competitive market; and, (2) intervention goals are well defined with an emphasis on profit maximization. The QLD government-owned generators meet the second criterion. They are legislated to have independent boards and management, which are tasked predominantly with profit maximization. For the first criterion, the efficiency of government versus private ownership depends heavily upon the degree of competition in the market. In particular, the purpose of government-owned companies in deregulated markets is obviated if there are no market failures. However, as we have shown, the QLD generation sector is not perfectly competitive. Ironically, it is the government-owned generators and their combined market share which both cause and exacerbate this market failure.

In this case, government ownership and market concentration appear to have conspired to produce an adverse outcome. As discussed in the Section 2.2 literature review, the desirability of public ownership is generally ambiguous. That said, the drop in wholesale prices at high demand levels associated with the Direction would not have been possible without government ownership. Since the QLD Government was the sole shareholder, the cost of intervention was low. In fact, the QLD Government notes, through its "Powering Queensland Plan" (2017*b*), that the Stanwell Direction was "only possible because electricity assets [were kept] in public hands." They go on to state that "[a]s a shareholder of electricity assets, [they] have the ability to take steps to counter some of the impacts in the broader national electricity market that [resulted] in higher wholesale prices and volatility during peak demand periods." Moreover, it could be argued that the Government's influence extended beyond its order to Stanwell. Vogelsang (1983) notes that a single state oligopolist may be able to act as a market leader and so reduce damage across the industry. Given the market structure, it is indeed highly likely that Stanwell acted as this leader in a way that made the exercise of market by other participants less profitable.

Government intervention occurring within the framework of government ownership, thus, can help redress a market failure. However, its wider market impacts are complex. For example, it can distort market signals, affecting long-term private sector investments (AER, 2018*b*). Actions imposed exclusively on government-owned companies could be considered discriminatory and provide a market advantage to one group of participants (Commission, 2016). As noted by the ACCC (2018), while the Direction to put downward pressure on wholesale prices improved short- and medium-term outcomes for consumers, interventions of this kind are not a substitute for structural reform. This point is underscored by the fact that despite the Direction, significant margins persisted at lower levels of demand.

In the context of QLD generation, the most direct and effective policy would be to restructure the industry through the disaggregation of government-owned generators. However, the QLD Government is incentivized to structure its generating assets as large portfolio generators, as it increases the probability of large and consistent dividends. The resultant decrease in competition is likely to harm efficiency and social welfare. Structural reforms promote efficiency but reduce dividends. For the Government, efficiency and fiscal objectives are clearly in conflict.

It should be noted that dividends from government-owned companies are returned to taxpayers as government services. As such, the associated harm is partly reduced, though non-competitive markets and market power still adversely impact allocative and technical efficiency. There are also potential equity implications, though the ex ante direction of the effects are ambiguous and would require further study. Thus, there is a potential misalignment between government and societal incentives. The government may be interested in improving its re-election prospects by using large dividends to fund social programs or enact tax cuts. The social planner would be concerned with maximizing welfare, which would necessitate correcting the market failure in the generation industry. When framed in this way, it is possible to view government ownership as a barrier to a less concentrated, more competitive generation market.

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Appendix

2.A. Model summary

This appendix describes the setup for the competitive benchmark model with endogenous interconnector flows. We first outline the optimization before defining all indices, constants and variables below.

Optimization

- **Maximize social welfare** W_t for all generation $q_{i,r,t}$ across unit i and region r during settlement interval t:

$$\max_{q_{i,r,t}} W_t = \sum_r \sum_i \Big[P_{r,t}(Q_{r,t}) - c_{i,r,t} \Big] \cdot q_{i,r,t}$$

$$\begin{array}{lrcll} s.t. & \tilde{z}_{i,r,t} - q_{i,r,t} & \geq & 0 & \forall \; i \in U \\ & q_{i,r,t} & \geq & 0 & \forall \; i \in U \\ & \tilde{T}^{im}_{l,t} - \sum_{r \in R^-} \phi_{r,l} \cdot y_{r,t} & \geq & 0 & \forall \; l \in L \\ & \sum_{r \in R^-} \phi_{r,l} \cdot y_{r,t} - \tilde{T}^{ex}_{l,t} & \geq & 0 & \forall \; l \in L \\ & \sum_{r \in R} y_{r,t} & = & 0 & \end{array}$$

  where the first and second constraints are for unit capacity and unit generation non-negativity, respectively. The remainder are flow import and export limits, as well as the conservation of net injections.

Indices

- **Units**: $i \in U$
- **Settlement intervals**: $t \in S$

- **Financial years**: $y \in Y$
- **Regions**: $r \in R = \{\text{VIC1}, \text{NSW1}, \text{QLD1}, \text{SA1}, \text{TAS1}\}$
- **Outregions**: $r \in R^{-} = \{\text{NSW1}, \text{QLD1}, \text{SA1}, \text{TAS1}\}$
- **Interconnectors**: $l \in L = \{\text{NSWQLD}, \text{TASVIC}, \text{VICNSW}, \text{VICSA}\}$

Exogenous variables

- **Assumed values**:
  - $\varepsilon = 0.1$ = price elasticity of demand
  - $\phi_{r,l}$ = distribution factor from injections to flows (Power Transfer Distribution Factors, PTFD)[78]

$$\boldsymbol{\phi} = \begin{array}{c} \begin{array}{cccc} \text{NSWQLD} & \text{TASVIC} & \text{VICNSW} & \text{VICSA} \end{array} \\ \begin{bmatrix} 0 & 0 & -1 & 0 \\ -1 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \\ 0 & 1 & 0 & 0 \end{bmatrix} \end{array} \begin{array}{l} \\ \text{NSW1} \\ \text{QLD1} \\ \text{SA1} \\ \text{TAS1} \end{array}$$

- **Market values**:[79]
  - $\tilde{P}_{r,t}$ = actual market price by region r and settlement interval t
  - $\tilde{Q}_{r,t}$ = actual market demand by region r and settlement interval t
  - $\tilde{x}_{r,t}$ = must-take generation by region r and settlement interval t, including semi-scheduled, non-scheduled, hydro and battery sources
  - $\tilde{z}_{i,r,t}$ = availability for unit i in region r and settlement interval t
  - $\tilde{T}^{im}_{l,t}$ = import limit across interconnector l and settlement interval t
  - $\tilde{T}^{ex}_{l,t}$ = export limit across interconnector l and settlement interval t

[78] Since the NEM is a radial network with VIC as the hub, all flows along lines l are define with respect to injections into VIC.

[79] These are exogenous values taken from actual market data from AEMO. See Appendix 2.B for a mapping of variable to source.

- **Non-market values**:[80]
  - VOM_i = variable operations and maintenance (VO&M) cost per MWh for unit i
  - HR_i = heat rate for unit i
  - $FP_{r,t}$ = fuel price for coal, gas or petroleum in region r and settlement interval t
  - $LF_{i,y} = MLF_{i,y} \cdot DLF_{i,y}$ = loss factor for unit i and financial year y, calculated as the product of the marginal loss factor (MLF) and the distribution loss factor (DLF).[81]

Endogenous variables

- **Demand curve** in region r and settlement interval t

$$\textbf{demand curve}: \qquad Q_{r,t}(P_{r,t}) = \alpha_{r,t} - \beta_{r,t} \cdot P_{r,t}$$

$$\textbf{inverse demand curve}: \qquad P_{r,t}(Q_{r,t}) = \frac{\alpha_{r,t}}{\beta_{r,t}} - \frac{1}{\beta_{r,t}} Q_{r,t}$$

- **Demand curve slope** defined using the actual market equilibrium in region r and settlement interval t

$$\beta_{r,t} = \varepsilon \left(\frac{\tilde{Q}_{r,t}}{|\tilde{P}_{r,t}|} \right)$$

- **Demand curve intercept** defined using the actual market equilibrium in region r and settlement interval t

$$\alpha_{r,t} = \tilde{Q}_{r,t} + \beta_{r,t} \cdot \tilde{P}_{r,t}$$

- **Simulated demand** in region r and settlement interval t, where $q_{i,r,t}$ is generation for unit i in region r and $y_{r,t}$ is net injections in region $r \in R^-$

$$Q_{r,t} = \sum_i q_{i,r,t} + \tilde{x}_{r,t} - y_{r,t}$$

[80] These are exogenous values taken from sources other than AEMO market data. See Appendix 2.B for a mapping of variable to source.

[81] The MLF represents average projected losses between the transmission node of the generator and the regional reference node. If the generator is connected to a distribution network, the DLF represents average projected losses between the generator and the transmission node of the distribution network.

- **Simulated price** from the inverse demand curve in region r and settlement interval t, where VIC1 is the hub and must be defined as the source of all net injections $y_{r,t} \ \forall \ r \in R^-$

$$
\begin{aligned}
P_{r,t}(Q_{r,t}) &= \frac{\alpha_{r,t}}{\beta_{r,t}} - \frac{1}{\beta_{r,t}} Q_{r,t} \\
&= \frac{\alpha_{r,t} - \sum_i q_{i,r,t} - \tilde{x}_{r,t} + y_{r,t}}{\beta_{r,t}} \\
P_{\text{VIC1},t}(Q_{r,t}) &= \frac{\alpha_{\text{VIC1},t} - \sum_i q_{i,\text{VIC1},t} - \tilde{x}_{\text{VIC1},t} - \sum_{r \in R^-} y_{r,t}}{\beta_{\text{VIC1},t}}
\end{aligned}
$$

- **Marginal cost** for unit i in region r and settlement interval t

$$
c_{i,r,t} = \frac{VOM_i + FP_{r,t} \cdot HR_i}{LF_{i,y}}
$$

- **Total cost** in region r and settlement interval t

$$
C_{r,t} = \sum_i c_{i,r,t} \cdot q_{i,r,t}
$$

2.B. Data summary

Table 2.B.1. Data source to variable mapping

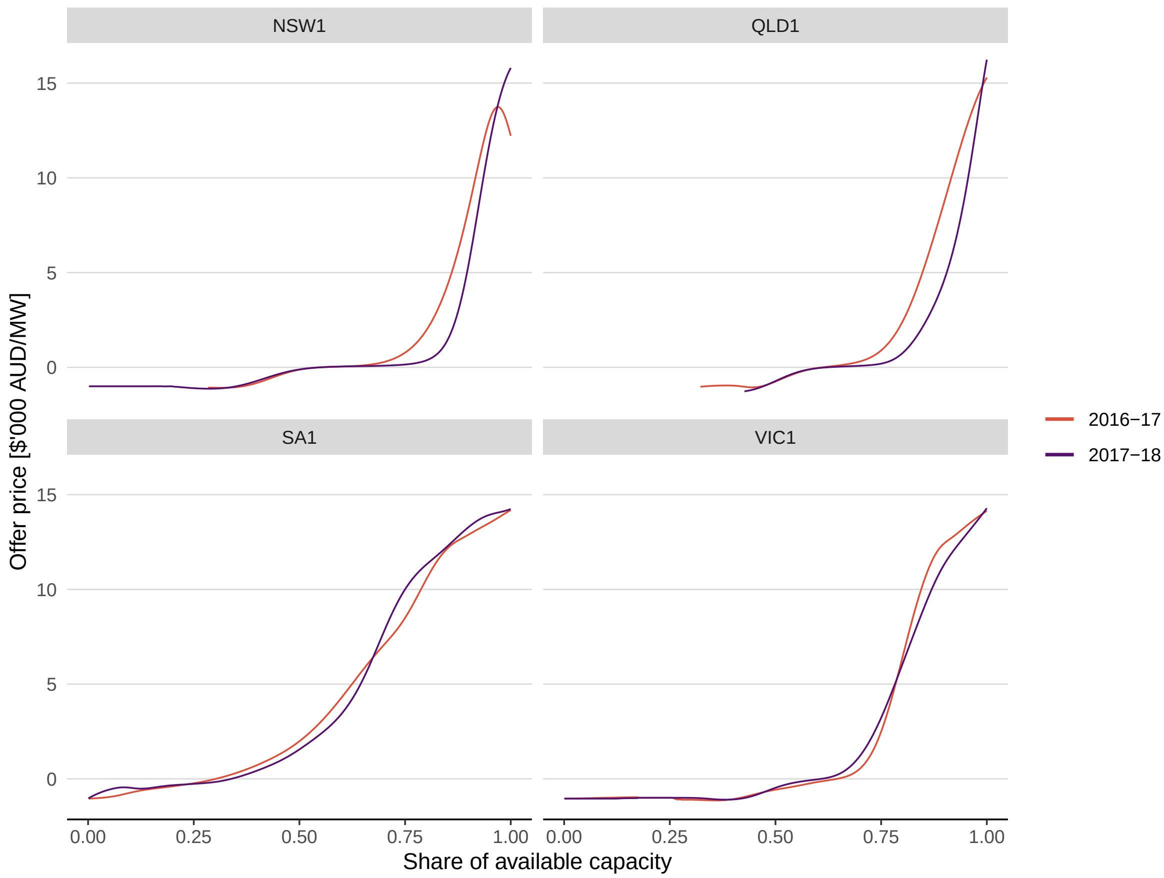
Variable	**Description**	**Source**
$\tilde{P}_{r,t}$	Regional Reference Price which serves as both an input to the intercept of the demand function and the price portion of the price-cost margin.	AEMO MMSDM (DISPATCHPRICE)
$\tilde{Q}_{r,t}$	Actual regional demand or load which serves as an input to the intercept of the demand function.	AEMO MMSDM (DISPATCHREGIONSUM)
$\tilde{q}_{i,r,t}$	Actual fossil-fired unit generation which serves as a comparison against our simulated unit outputs $q_{i,r,t}$.	AEMO MMSDM (DISPATCHLOAD)
$\tilde{z}_{i,r,t}$	Fossil-fired unit availabilities which serve as the constraint on unit generation.	AEMO MMSDM (DISPATCHLOAD)
$\tilde{x}_{r,t}$	Must-take generation—i.e. non-scheduled generation, hydro, solar, wind, batteries, and raise regulation—which serves as an exogenous portion of demand $Q_{r,t}$.	AEMO MMSDM (DISPATCHREGIONSUM, DISPATCHLOAD & DISPATCHINTERCONNECTORRES)
$\tilde{F}_{l,t}$	Actual interconnector flows which serves as a comparison against our simulated regional flows $F_{l,t}$.	AEMO MMSDM (DISPATCHINTERCONNECTORRES)
$\tilde{T}_l^{im}$	Actual interconnector import limits which serves in the optimization problem flow constraints.	AEMO MMSDM (DISPATCHINTERCONNECTORRES)
$\tilde{T}_l^{ex}$	Actual interconnector export limits which serves in the optimization problem flow constraints.	AEMO MMSDM (DISPATCHINTERCONNECTORRES)
$MLF_{i,y}$	Marginal loss factors which serve as an input to the marginal cost curve.	AEMO MMSDM (DUDETATILSUMMARY)
$DLF_{i,y}$	Distribution loss factors which serve as an input to the marginal cost curve.	AEMO MMSDM (DUDETATILSUMMARY)
VOM_i	Variable operations and maintenance costs per MWh which serve as an input to marginal cost.	AEMO ISP & NTNDP (Fuel & Technology Cost Review)
HR_i	Heat rates in GJ/MWh which serve as an input to marginal cost.	AEMO ISP & NTNDP (Fuel & Technology Cost Review)
$FP_{r,t}^{i \in black\ coal}$	Marginal cost of black coal in \$AUD/GJ, which serves as an input to the marginal cost curve and is calculated as the quotient of price over energy content.	Bloomberg (COASNE60); DEE (2017)

Variable	Description	Source
$FP_{r,t}^{i\,\in\,brown\ coal}$	Marginal cost of brown coal in \$AUD/GJ, which serves as an input to the marginal cost curve and is calculated as the product of price and brown-to-black coal price ratio over energy content.	Bloomberg (COASNE60); AEMO ISP (Coal & Biomass price); DEE (2017)
$FP_{r,t}^{i\,\in\,natural\ gas}$	Marginal cost of brown coal in \$AUD/GJ, which serves as an input to the marginal cost curve and is calculated as the sum of price and haulage.	AEMO DWGM & STTM; Gas Transmission Tariffs
$FP_{r,t}^{i\,\in\,diesel}$	Marginal cost of diesel in \$AUD/GJ, which serves as an input to the marginal cost curve and is calculated as the quotient of price over energy content.	AIP (Diesel TGP); DEE (2017)
$FP_{r,t}^{i\,\in\,kerosene}$	Marginal cost of kerosene in \$AUD/GJ, which serves as an input to the marginal cost curve and is calculated as the quotient of price over energy content. Price is inferred from the standard excise taxes and the spread between Signaporean kerosene and diesel.	Bloomberg (GASL500P & JETKSPOT); DEE (2017)
i	Unit names, ids and characteristics – such as, fuel type and description, technology, capacity, etc. – which serve to permit identification, merging and extrapolation across the various datasets.	AEMO Registration & Exemptions List; AEMO MMSDM (DUDETAIL & DUDETATILSUMMARY)
l	Interconnector names, ids and characteristics – such as, capacity limits, etc. – which serve to permit identification, merging and extrapolation across the various datasets.	AEMO MMSDM (DISPATCHINTERCONNECTORRES); AEMO (2017)

Notes: The acronyms in the "Source" column are defined as follows: AEMO = Australian Energy Market Operator; DEE = Department of the Environment and Energy; ISP = Integrated System Plan; MMSDM = Market Management System Data Model; and, NTNDP = National Transmission Network Development Plan.

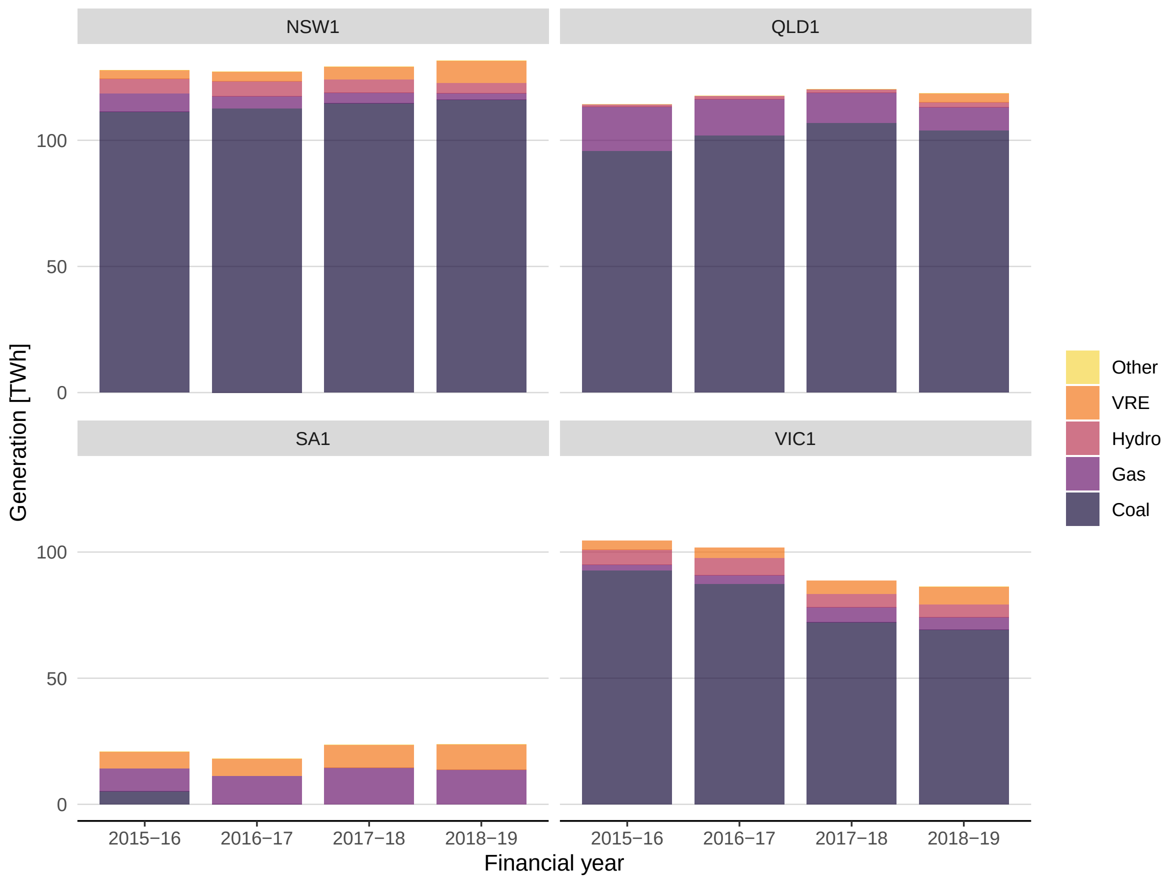
2.C.1. Descriptive outputs

Figure 2.C.1. Normalized offer curves by region and financial year.



Notes: This plot presents average relative offer curves by region during the 2016-17 and 2017-18 financial years. The 2016-17 financial year curve occurred prior to the QLD Government's "Stanwell Direction." The curves are local polynomial regressions using a normal kernel with a 0.04 bandwidth. Some curves do not extend back to zero on the quantity axis since there are no no points in those areas. It should be assumed that all curves extend back horizontally until (0, -1,000).

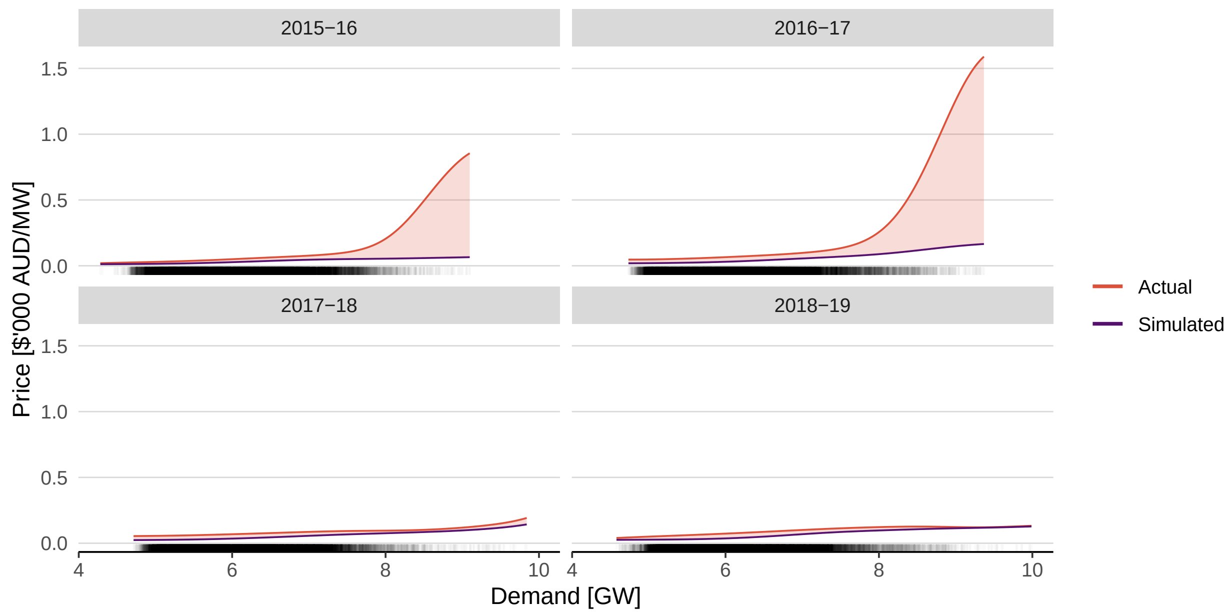
FIGURE 2.C.2. Total generation by region, technology and financial year.



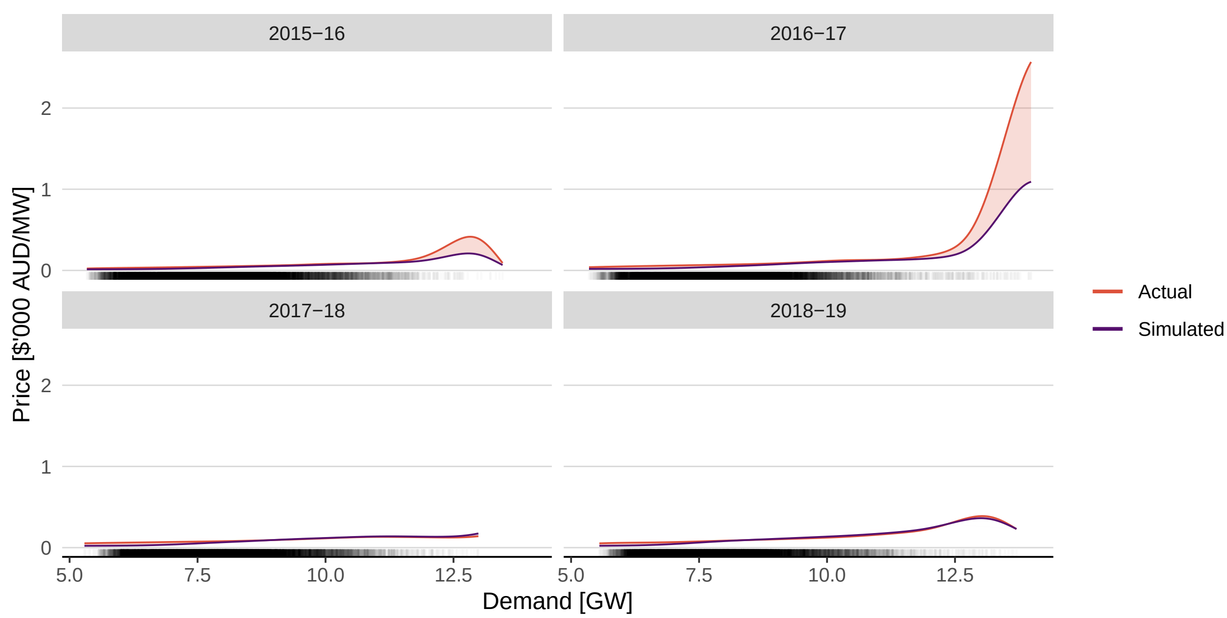
Notes: This plot presents total generation by region and technology between the 2015-16 and 2018-19 financial years. Variable renewable energy (VRE) includes large-scale solar and on-shore wind. Other includes liquid fuels and biomass. We do not account for the regional interconnector capacities, nor for roof-top solar installations which are significant in Australia. An equivalent plot presenting generation capacity by region, technology and financial year is presented in Figure 2.2 in the text.

2.C.2. Analytic outputs

FIGURE 2.C.3. Price-cost margins by region and financial year.



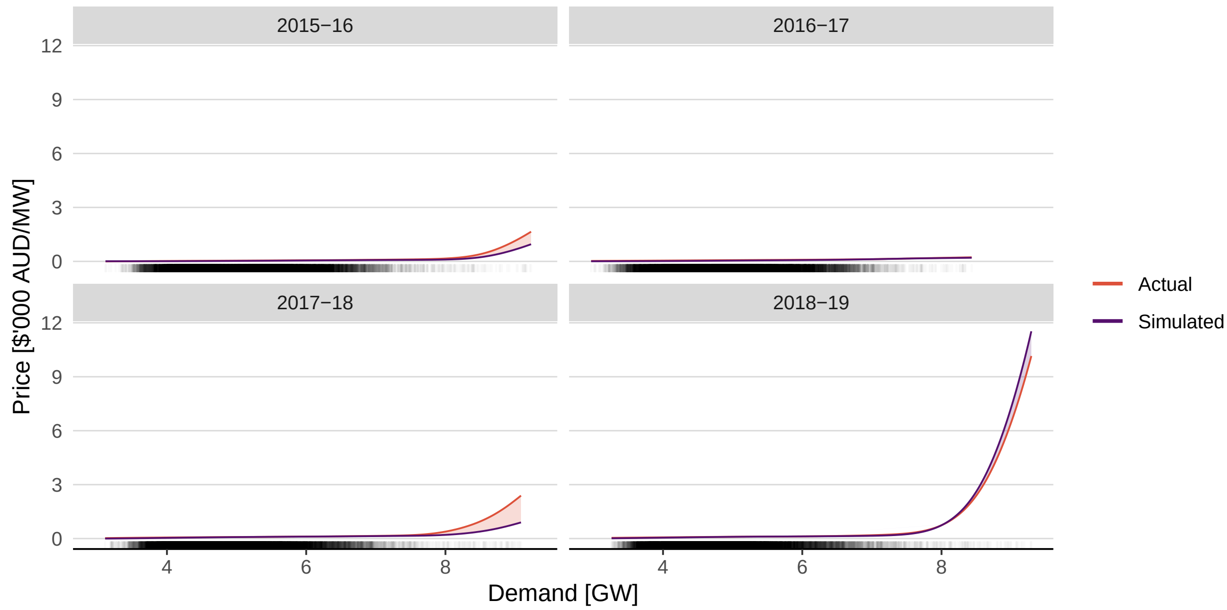
(a) QLD.



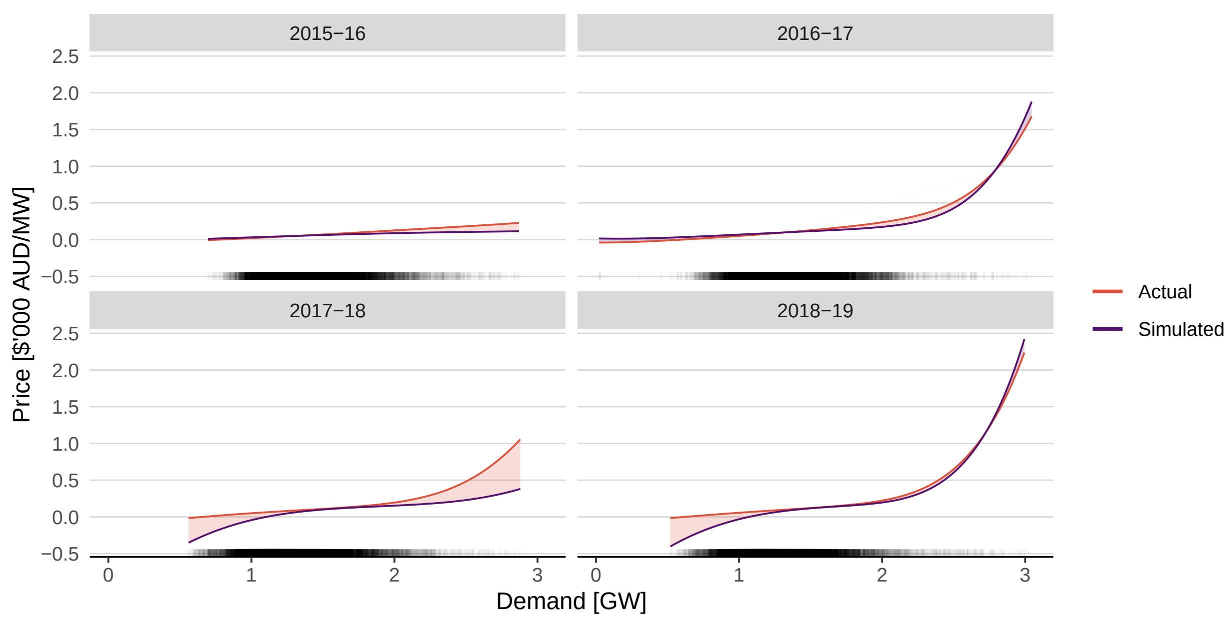
(b) NSW.

Notes: See below.

Figure 2.C.3. Price-cost margins by region and financial year (cont).



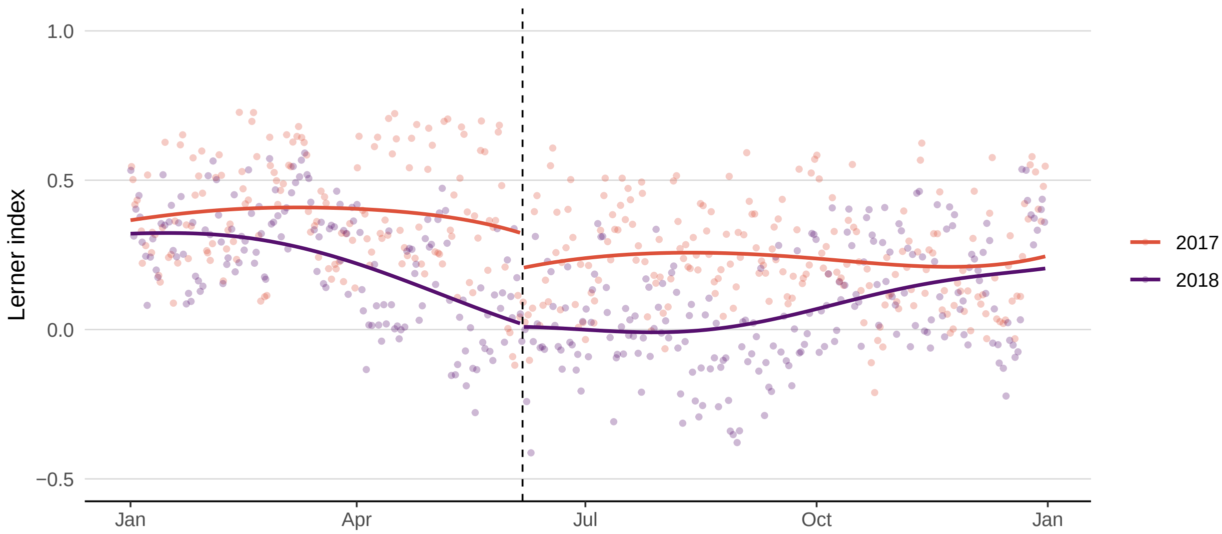
(c) VIC.



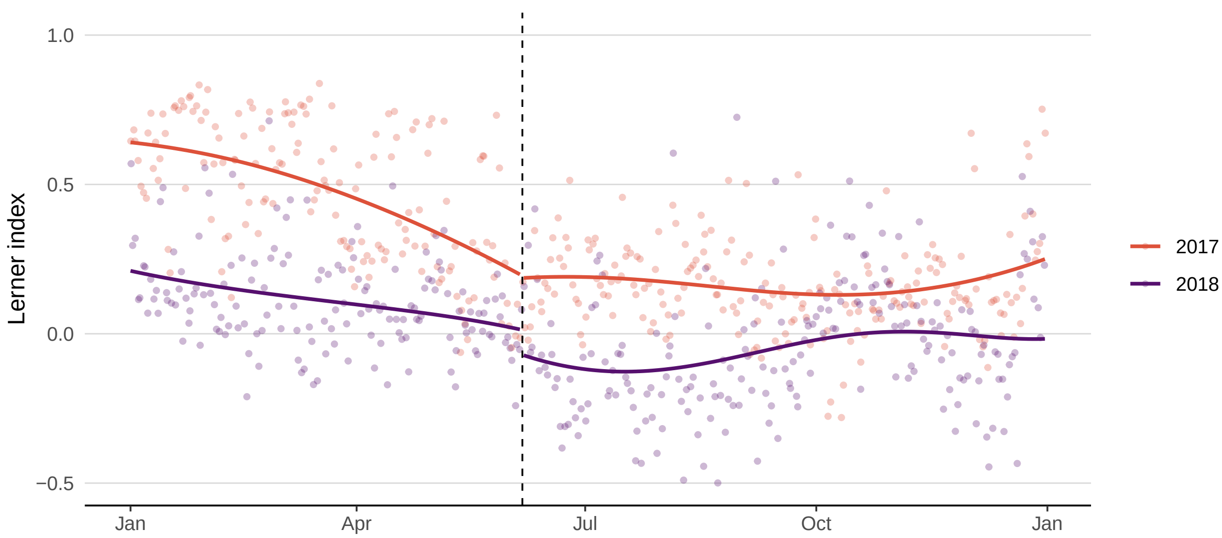
(d) SA.

Notes: This plot is the full-range companion to Figure 2.1 in the text. It presents non-parametric means of actual versus simulated prices by region and financial year. The shaded area between the two prices curves represents the average price-cost margin for the particular level of regional demand. Actual prices are based on RRPs from AEMO, while simulated prices are generated using a multistate model with endogenous transmission flows. The price curves are local polynomial regressions using a normal kernel with a 500 MW bandwidth. The black lines along the horizontal axis provide the density of actual demand.

Figure 2.C.4. Daily average Lerner index values by region and calendar year.



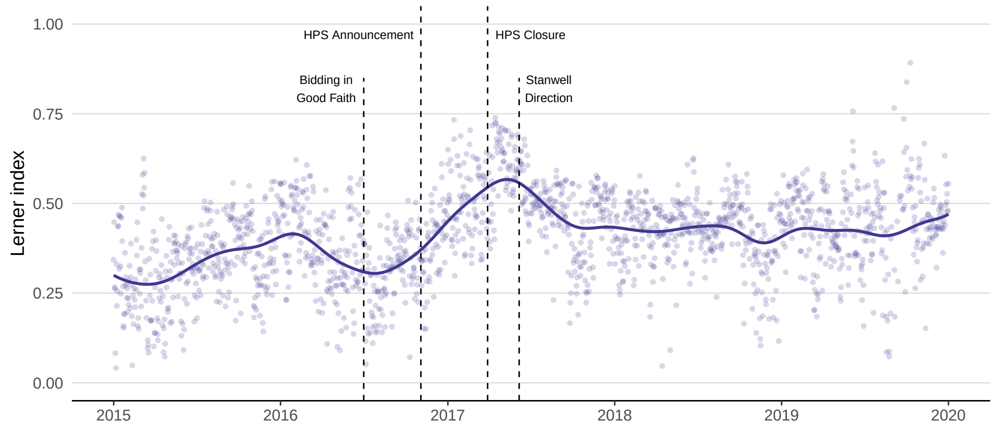
(a) NSW.



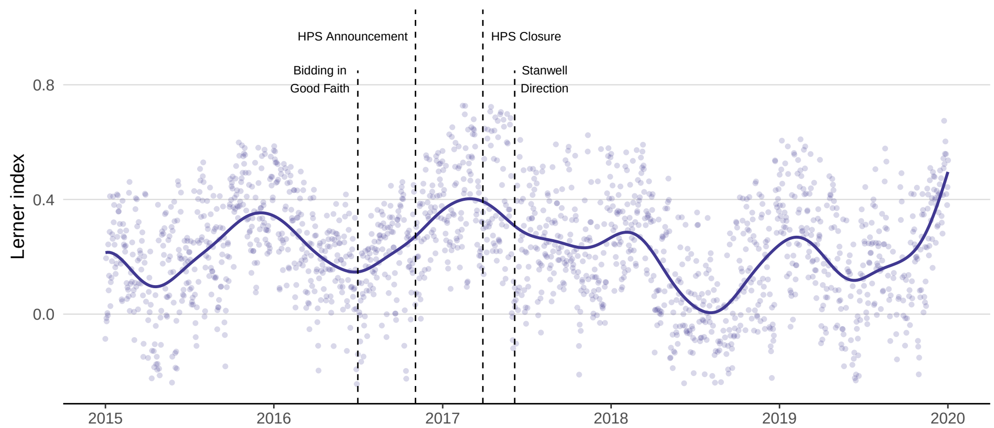
(b) VIC.

Notes: This plot is the companion to Figure 2.2 in the text. It presents daily average Lerner index values for NSW and VIC during the 2017 and 2018 calendar years. Lerner index values are based on actual market outcomes from AEMO and simulated runs from a multistate model with endogenous transmission flows. The vertical dashed line identifies the date of the QLD Government's "Stanwell Direction" which occurred on 6 June 2017. The curves are local polynomial regressions using a normal kernel with a 45 day bandwidth. They serve to highlight that, after the Direction in 2017, relative markups decreased in NSW and remained level in VIC. This is perhaps to be expected given that QLD and NSW are neighbors and likely impact each other far more significantly than QLD and VIC.

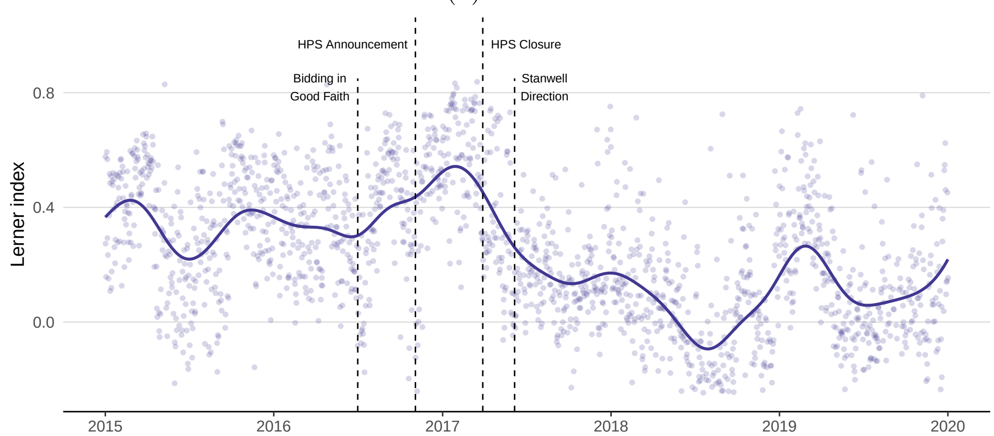
Figure 2.C.5. Daily average Lerner index values between 2015 and 2019 by region.



(a) QLD.



(b) NSW.



(c) VIC.

Notes: This plot presents daily average Lerner index values between 2015 and 2019. Lerner index values are based on actual market outcomes from AEMO and simulated runs from a multistate model with endogenous transmission flows. The vertical dashed lines identify major events in the leadup to the QLD Government's "Stanwell Direction" which occurred on 6 June 2017. The curves are local polynomial regressions using a normal kernel with a 45 day bandwidth.

Figure 2.C.6. Monthly total revenue by region between 2015 and 2019.

Notes: This plot presents monthly total revenue by region between 2015 and 2019. Actual revenues are based on market prices and quantities from AEMO, while simulated revenues are generated using a multistate model with endogenous transmission flows. Grey vertical line signifies the institution of the "Bidding in Good Faith" provision, while the black vertical line signifies the 2017 "Stanwell Direction" from the QLD Government.

Table 2.C.1. Actual price, simulated marginal cost and difference in profits by month

Month	*Actual*			*Simulation*			
	Generation	**Price**	**Profit**	**Generation**	**Price**	**Profit**	**ΔProfit**
	[MW]	[$AUD/MW]	[$million AUD]	[MW]	[$AUD/MW]	[$million AUD]	[$million AUD]
Panel A: NSW							
2015-07	7,519	39.2	288.72	8,734	32.8	270.64	18.07
2015-08	7,044	36.8	247.04	8,366	29.2	218.73	28.31
2015-09	6,733	58.0	436.23	7,424	36.7	265.66	170.58
2015-10	6,426	36.7	232.61	7,567	20.5	100.98	131.63
2015-11	6,546	46.0	332.55	7,612	30.6	214.59	117.96
2015-12	6,686	44.6	309.78	7,928	29.0	207.93	101.85
2016-01	6,513	45.2	335.56	7,849	27.8	194.99	140.57
2016-02	7,347	38.8	275.42	8,637	27.5	195.95	79.47
2016-03	6,883	44.6	323.80	7,592	35.8	270.83	52.97
2016-04	5,954	66.1	444.28	6,405	51.9	353.42	90.86
2016-05	6,394	67.2	520.74	6,915	52.8	413.06	107.68
2016-06	6,943	97.5	849.21	7,670	86.5	802.62	46.59
2016-07	7,209	65.9	534.45	8,485	64.7	590.46	−56.01
2016-08	7,244	48.2	356.07	8,682	38.0	291.29	64.78
2016-09	6,426	44.8	259.27	7,476	36.6	218.57	40.70
2016-10	4,976	55.4	279.93	6,147	44.5	251.53	28.40
2016-11	5,591	83.1	533.22	6,631	51.1	321.15	212.06
2016-12	6,268	51.7	340.63	7,746	31.6	186.06	154.57
2017-01	7,562	82.6	776.97	8,727	53.5	502.21	274.76
2017-02	7,169	170.6	1,673.53	8,634	102.3	1,049.01	624.52
2017-03	6,906	92.9	783.00	8,357	58.4	508.09	274.91
2017-04	6,179	106.5	767.26	7,650	62.2	502.39	264.88
2017-05	7,153	89.6	753.18	8,528	55.4	489.28	263.90
2017-06	7,741	84.8	732.83	8,871	73.6	708.84	23.99
2017-07	7,570	91.2	798.14	9,067	68.6	639.55	158.59
2017-08	6,619	102.2	802.12	8,092	79.0	699.12	103.00
2017-09	5,987	87.0	544.94	7,618	63.7	471.55	73.38
2017-10	6,215	81.6	551.68	7,458	67.5	497.08	54.60
2017-11	6,712	78.7	550.14	7,647	64.2	468.38	81.76
2017-12	7,197	76.4	596.34	8,174	61.1	497.33	99.00
2018-01	7,542	75.8	632.68	8,580	58.2	493.02	139.66
2018-02	7,317	72.4	516.54	8,442	50.4	351.85	164.69
2018-03	6,762	66.2	467.94	7,998	42.7	272.93	195.01
2018-04	6,039	73.5	466.82	6,910	66.3	457.52	9.30
2018-05	6,456	76.8	550.40	7,410	74.4	584.51	−34.11
2018-06	7,011	100.5	796.15	7,745	100.1	850.45	−54.30
2018-07	6,993	74.5	556.27	7,972	75.4	624.12	−67.85
2018-08	6,282	92.3	657.46	7,030	103.9	831.91	−174.45
2018-09	6,299	93.1	650.73	7,006	94.6	712.71	−61.98
2018-10	6,369	88.0	633.73	6,993	75.5	552.61	81.12
2018-11	6,767	85.9	626.07	7,321	75.7	562.74	63.33
2018-12	6,669	82.0	608.07	7,610	71.7	553.42	54.65
2019-01	7,881	117.6	1,183.03	8,959	90.9	955.46	227.57

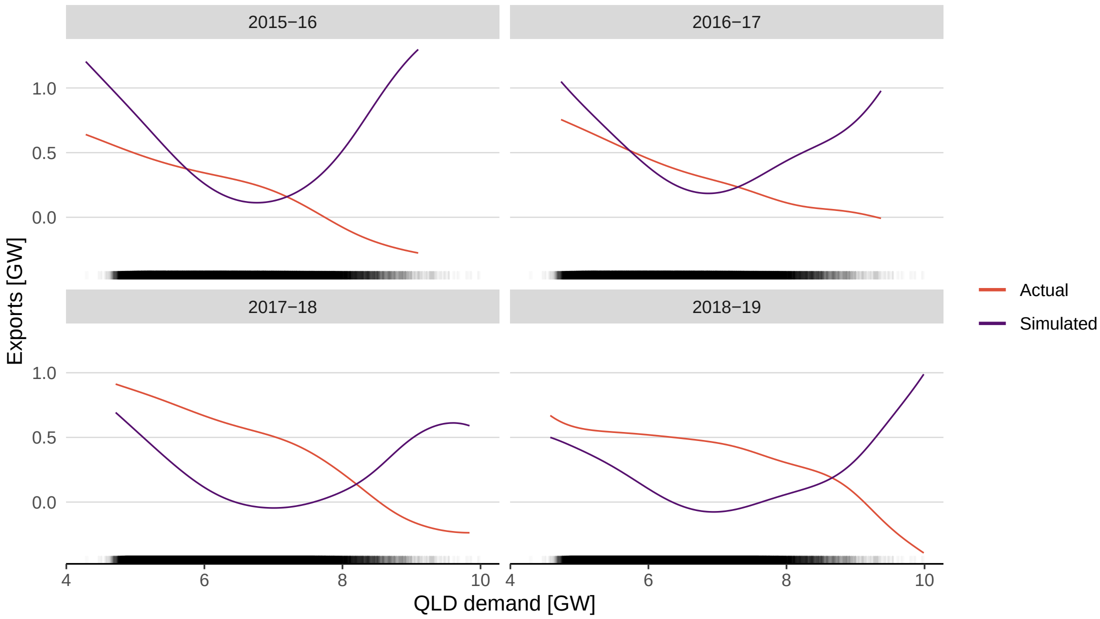
	Actual			*Simulation*			
Month	**Generation**	**Price**	**Profit**	**Generation**	**Price**	**Profit**	**ΔProfit**
	[MW]	[$AUD/MW]	[$million AUD]	[MW]	[$AUD/MW]	[$million AUD]	[$million AUD]
2019-02	7,192	89.2	661.72	8,402	59.1	434.04	227.68
2019-03	6,730	87.6	660.67	7,715	66.6	519.11	141.56
2019-04	6,239	77.5	513.71	7,280	66.0	459.49	54.22
2019-05	6,687	79.1	581.31	7,532	77.1	611.59	−30.29
2019-06	7,228	91.0	729.88	8,155	96.4	851.81	−121.93
Panel B: QLD							
2015-07	6,325	46.7	276.38	5,724	24.5	110.20	166.18
2015-08	6,141	40.3	215.96	5,523	23.4	91.69	124.27
2015-09	5,988	44.8	235.00	5,752	27.8	124.23	110.76
2015-10	6,101	36.4	171.89	5,440	21.0	68.99	102.90
2015-11	6,730	45.4	279.25	6,010	26.8	125.52	153.73
2015-12	6,781	43.1	250.19	6,047	25.6	122.27	127.93
2016-01	6,564	51.5	330.52	6,003	27.4	142.39	188.13
2016-02	6,735	121.3	1,067.06	6,326	29.3	156.84	910.23
2016-03	6,627	70.9	503.57	6,544	30.4	176.82	326.75
2016-04	6,516	66.6	439.29	6,577	41.1	257.83	181.46
2016-05	6,192	69.6	466.98	6,058	44.7	275.12	191.86
2016-06	6,766	87.4	645.50	6,377	52.4	360.57	284.93
2016-07	6,616	60.8	347.53	5,878	44.2	253.45	94.09
2016-08	6,331	48.0	250.68	5,623	32.1	132.61	118.07
2016-09	6,216	46.0	216.96	5,702	30.1	105.07	111.89
2016-10	6,225	53.9	297.44	5,812	33.4	142.61	154.83
2016-11	6,721	69.4	439.27	6,231	44.2	245.27	194.01
2016-12	6,694	67.5	426.48	5,905	34.9	165.25	261.23
2017-01	7,034	199.5	1,941.36	6,641	50.1	345.74	1,595.62
2017-02	7,434	232.1	2,200.35	6,817	65.9	468.37	1,731.98
2017-03	7,028	89.0	648.35	6,450	43.3	253.24	395.11
2017-04	6,439	94.8	612.60	5,836	38.5	181.55	431.05
2017-05	6,323	86.2	562.89	5,921	34.9	161.24	401.65
2017-06	6,741	76.4	510.62	6,231	33.9	152.73	357.89
2017-07	6,769	77.6	522.74	6,039	39.2	169.19	353.55
2017-08	6,718	81.8	565.20	6,107	41.9	195.09	370.11
2017-09	6,363	80.4	497.95	5,928	45.6	207.14	290.82
2017-10	6,298	77.4	459.67	5,906	49.9	239.71	219.96
2017-11	6,856	65.3	381.31	6,359	36.1	135.79	245.52
2017-12	7,018	71.4	463.87	6,532	38.0	167.51	296.35
2018-01	7,186	72.7	461.40	6,620	47.0	257.22	204.18
2018-02	7,104	71.6	420.72	6,547	40.9	184.11	236.61
2018-03	6,942	62.1	351.14	6,293	37.0	156.89	194.26
2018-04	6,740	62.9	342.43	6,363	37.0	142.21	200.22
2018-05	6,621	64.8	373.29	6,109	35.8	137.51	235.78
2018-06	6,833	80.2	525.21	6,350	41.0	187.99	337.21
2018-07	6,415	68.8	399.73	6,116	40.4	171.59	228.14
2018-08	6,386	81.8	516.55	6,179	48.1	236.79	279.77
2018-09	6,342	80.4	492.74	6,028	41.0	158.98	333.76
2018-10	6,278	78.1	479.25	6,047	47.2	226.26	253.00

	Actual			*Simulation*			
Month	**Generation** [MW]	**Price** [$AUD/MW]	**Profit** [$million AUD]	**Generation** [MW]	**Price** [$AUD/MW]	**Profit** [$million AUD]	**ΔProfit** [$million AUD]
2018-11	6,227	88.8	543.41	6,004	64.6	368.99	174.42
2018-12	6,623	78.3	509.80	6,088	49.7	267.01	242.79
2019-01	6,998	94.0	662.48	6,480	50.9	289.21	373.27
2019-02	6,792	83.9	482.12	6,385	44.3	194.01	288.11
2019-03	6,884	80.7	501.79	6,440	51.7	282.95	218.84
2019-04	6,212	68.0	368.05	5,678	37.2	128.53	239.52
2019-05	6,103	72.8	411.17	5,809	44.1	192.00	219.16
2019-06	6,193	84.7	506.27	5,730	44.9	189.33	316.94
Panel C: VIC							
2015-07	5,943	34.7	225.98	5,719	29.0	180.16	45.82
2015-08	5,450	35.2	208.80	5,422	29.4	167.07	41.73
2015-09	5,243	44.5	259.38	5,162	31.8	167.54	91.84
2015-10	5,230	35.5	204.15	4,938	16.7	59.90	144.25
2015-11	5,286	35.1	195.11	5,000	20.9	89.29	105.82
2015-12	5,325	48.0	308.69	5,246	30.6	175.97	132.72
2016-01	5,426	46.9	339.13	5,525	30.1	199.36	139.78
2016-02	5,440	35.4	198.70	5,398	26.1	130.74	67.97
2016-03	5,495	45.8	300.19	5,365	29.8	167.88	132.32
2016-04	5,460	45.8	293.22	5,372	30.9	177.23	116.00
2016-05	5,096	54.8	355.71	5,176	38.2	235.90	119.82
2016-06	5,444	92.4	641.50	5,659	67.0	465.45	176.05
2016-07	5,046	64.5	392.66	5,141	55.5	343.89	48.77
2016-08	5,382	43.3	271.92	5,399	25.4	138.35	133.57
2016-09	5,276	41.0	237.01	5,008	18.6	73.76	163.25
2016-10	4,965	33.2	178.44	4,788	22.6	103.73	74.71
2016-11	5,258	36.1	207.11	5,049	23.8	113.73	93.38
2016-12	5,417	29.9	169.99	4,757	11.4	20.44	149.55
2017-01	5,578	62.1	428.18	4,908	25.2	132.44	295.74
2017-02	5,460	86.3	552.61	5,022	48.7	295.19	257.42
2017-03	5,392	90.9	607.77	4,906	46.8	260.39	347.38
2017-04	4,873	108.1	610.96	4,437	65.9	352.52	258.44
2017-05	4,527	108.0	597.63	4,245	81.7	433.23	164.41
2017-06	5,037	98.7	580.66	4,788	86.6	513.78	66.87
2017-07	4,369	117.4	627.22	4,231	94.5	489.61	137.61
2017-08	4,804	102.3	615.69	4,801	84.5	505.91	109.78
2017-09	4,399	78.5	412.55	4,414	73.0	388.91	23.64
2017-10	4,123	72.8	365.10	4,283	66.8	334.83	30.27
2017-11	4,169	95.4	471.21	4,275	81.8	398.56	72.65
2017-12	4,332	84.3	450.42	4,455	68.7	362.32	88.10
2018-01	4,681	125.2	855.97	4,638	87.3	548.43	307.54
2018-02	4,628	96.2	544.98	4,669	77.4	411.09	133.89
2018-03	4,140	74.9	379.51	4,146	69.9	353.40	26.11
2018-04	4,459	71.1	380.70	4,446	67.5	362.15	18.55
2018-05	4,597	78.2	443.36	4,517	73.0	414.25	29.10
2018-06	4,855	93.3	547.96	4,933	101.3	611.98	−64.03
2018-07	4,584	69.4	395.80	4,697	81.0	478.37	−82.57

Month	*Actual* Generation [MW]	*Actual* Price [$AUD/MW]	*Actual* Profit [$million AUD]	*Simulation* Generation [MW]	*Simulation* Price [$AUD/MW]	*Simulation* Profit [$million AUD]	ΔProfit [$million AUD]
2018-08	4,492	78.9	443.86	4,642	89.7	524.18	−80.32
2018-09	3,979	91.2	435.25	4,180	98.4	477.31	−42.06
2018-10	3,949	99.4	499.34	3,933	84.2	417.67	81.67
2018-11	3,733	96.5	438.45	3,821	99.4	456.86	−18.41
2018-12	4,114	90.5	475.25	4,212	90.9	472.41	2.84
2019-01	4,508	238.0	1,668.91	4,471	238.6	1,738.82	−69.91
2019-02	4,452	110.7	576.19	4,264	68.7	332.50	243.70
2019-03	4,617	130.6	867.03	4,472	74.3	447.69	419.34
2019-04	3,906	95.3	439.30	3,800	80.4	368.84	70.46
2019-05	4,028	91.6	430.84	3,994	93.7	454.89	−24.05
2019-06	4,449	100.9	552.13	4,517	95.2	522.58	29.55

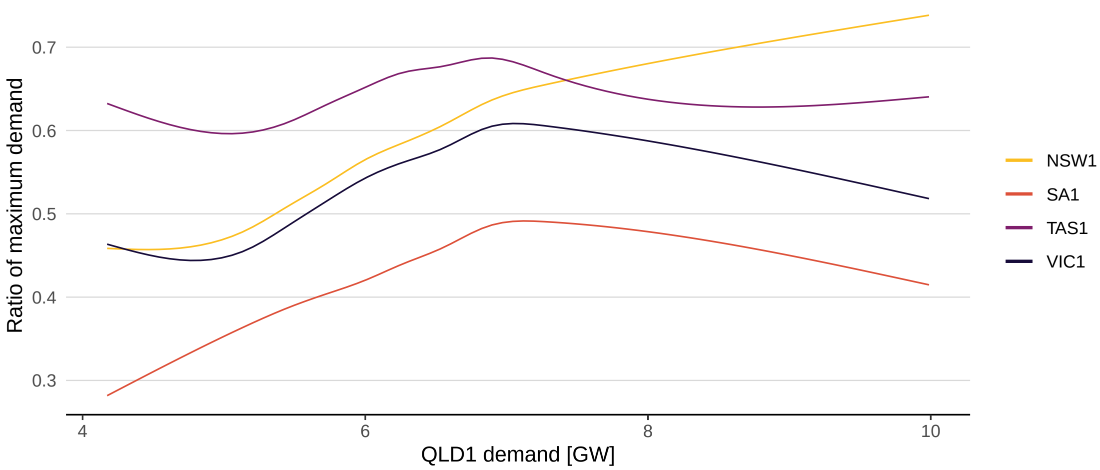
Notes: This table is the companion to Table 2.1 in the text. It presents the difference between actual and simulated profits at the monthly level. For each generator and settlement interval, profits are calculated as the product of unit generation and the difference between price and marginal cost. These are then summed over all units and intervals to arrive at an estimate for the monthly, actual and simulated profits and their difference.

Figure 2.C.7. Export densities from QLD between 2015 and 2019.



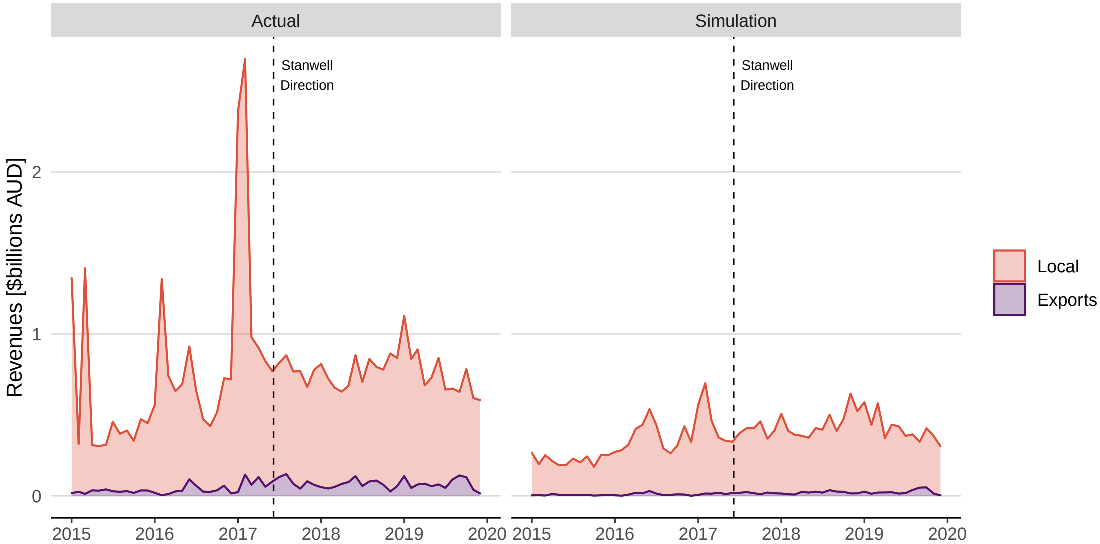
Notes: This plot presents non-parametric means of QLD export densities versus QLD actual demand by financial year. Actual export and demand values are based on market outcomes from AEMO, while simulated exports are from a multistate model with endogenous transmission flows. The curves are local polynomial regressions using a normal kernel with a 500 MW bandwidth. The black lines along the horizontal axis provide the density of actual demand.

Figure 2.C.8. Export densities from QLD by financial year.



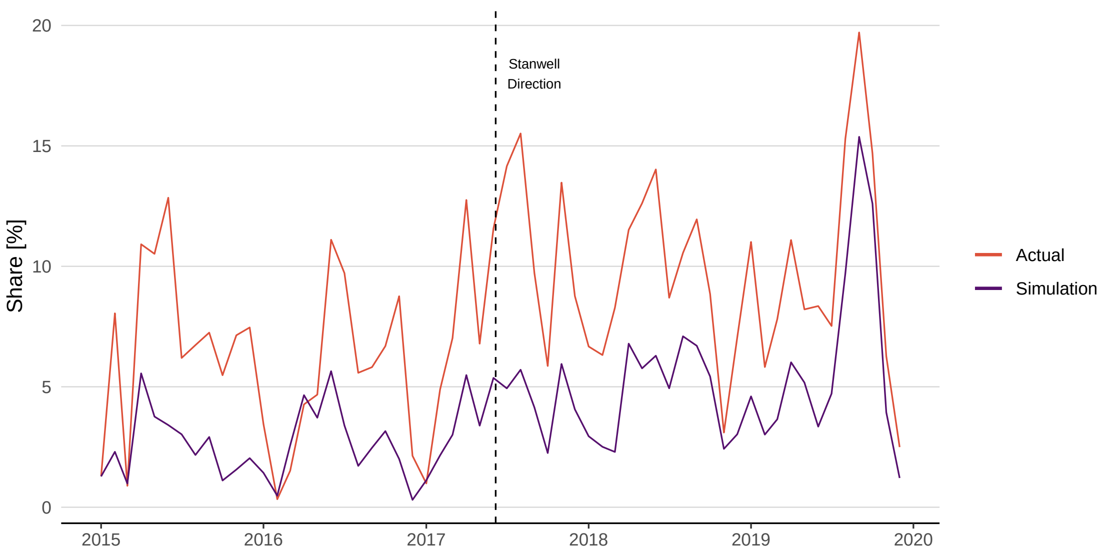
Notes: This plot presents non-parametric means of QLD demand versus the ratio of maximum demand in the other NEM regions between 2015 and 2019. Demand values are based on market outcomes from AEMO. The curves are GAM regressions.

FIGURE 2.C.9. Monthly revenues in QLD from local and export demand between 2015 and 2019.



Notes: This plot presents monthly revenues in QLD from local versus export demand between 2015 and 2019. Actual revenues are based on market prices and quantities from AEMO, while simulated revenues are generated using a multi-state model with endogenous transmission flows. The dashed vertical line represents the QLD Government's "Stanwell Direction" which occurred on 6 June 2017.

FIGURE 2.C.10. Share of monthly revenues in QLD from exports between 2015 and 2019.



Notes: This plot presents the share of monthly revenues in QLD from exports compared to total revenues between 2015 and 2019. Actual revenues are based on market prices and quantities from AEMO, while simulated revenues are generated using a multi-state model with endogenous transmission flows. The dashed vertical line represents the QLD Government's "Stanwell Direction" which occurred on 6 June 2017.

CHAPTER 3

Still your grandfather's boiler: Estimating the effects of the Clean Air Act's grandfathering provisions

Co-Authors:

Sylwia Bialek and Richard L. Revesz

3.1. Introduction

Policymakers can condition regulatory stringency on the vintage of regulated units, with later entrants typically being subject to more stringent standards. Such vintage differentiated regulation (VDR) is common practice, especially within environmental regulations. Grandfathering constitutes a special form of VDR, where incumbents are exempted from new regulation.

Differentiating regulation by unit age mitigates the impacts of new regulations for pre-existing units, which may reduce investment uncertainty among future investors (Kaplow, 1986). It can, in some cases, be justified on the grounds of efficiency or fairness (Nash, 2009). However, differentiation may also lead to distortions, described as "new source bias" (Levinson, 1999). For instance, as differentiation tends to increase the relative cost of new units, it can lead to their decreased operation and profitability. All else being equal, this can reduce the number of new entrants and lengthen the lifespan of existing units (Fraas, Graham and Holmstead, 2017; Heutel, 2011; Revesz and Westfahl Kong, 2011).[1] Thus, in researching differentiated regulations, the interesting question is not whether unintended consequences occur, but what is the economic significance of these consequences.

Despite its high prevalence[2] and the potential for perverse effects,[3] VDR remains understudied in economics (Damon et al., 2019). This is true even in the context of the Clean Air Act, a seminal US environmental statute that has been touted as "one of the most significant federal interventions into markets in the postwar period" (Currie and Walker, 2019). While the statute consists of many elements, New Source Review (NSR) is a key component that affects virtually every major manufacturing facility and power plant in the US, both those existing and constructed in the future. This stringent and complex permitting process, introduced in 1977 (Fraas, Graham and Holmstead,

[1] These effects can be partially mitigated through the greater regulatory uncertainty—and thus, greater operational risk—that grandfathered incumbents may face. For these units, future, more stringent regulations passed without grandfathering provisions may be very hard to meet an thus can can affect the profits particularly negatively.

[2] As Stavins (2006) notes, in the US, VDR appears "within the Clean Air Act in its standards for emissions from new versus existing stationary sources, motor vehicle and motor vehicle engines, non-road engines and vehicles, and commercial vehicles; within the Clean Water Act in a wide variety of aspects, including in effluent limits for public treatment plants; within the Safe Drinking Water Act; and within laws affecting the generation and disposal of hazardous and solid waste ... in a variety of occupational health and safety laws, automotive safety regulations, consumer product safety laws, and building codes." Vintage-differentiation is present also in drug approvals, underground storage tanks regulations, the Consumption Tax Act, the Affordable Care Act, Federal Communications Commission's multiple ownership rules, financial regulations like SHO Rule 201, etc.

[3] In the environmental context, new source bias combined with lower efficiency and higher emission rates from incumbents, suggest that certain types of VDR could even increase aggregate emissions (Gruenspecht, 1982).

2017), only applies to new units and to existing units having undergone substantial modifications. Despite the high compliance costs of NSR provisions, they have largely escaped comprehensive and rigorous retrospective analyses (Aldy et al., 2020).

In this paper, we are interested in the consequences of NSR grandfathering provisions. We study them empirically in the context of coal power plants, examining how grandfathering affected the survival of boilers, their utilization, and their emissions rates. We narrow our analysis to coal boilers for two reasons. First, the effects of NSR grandfathering on the power plant fleet has been particularly controversial in the US (Revesz and Lienke, 2016). Second, NSR was drafted with the aim of limiting the highly damaging sulfur dioxide (SO_2), for which coal power plants were the main emitter.[4]

As the NSR design differs somewhat between non-attainment counties—those counties who have not met federal air quality standards—and attainment counties, which are in compliance with such standards, we investigate whether the grandfathering effects change depending on county attainment status. This is particularly relevant as sulfur pollution is non-uniformly mixed, meaning associate health and environmental damages depend on the location of the emissions source (Fowlie and Muller, 2019).[5] In non-attainment counties, emissions are already more concentrated, so a stronger new source bias in these areas would constitute an important design flaw in NSR.

In this paper, we thus explore how coal boiler owners responded to NSR grandfathering provisions and to related regulatory regime by adjusting boiler utilization, survival and sulfur emissions. We compare the outcomes for grandfathered boilers and boilers subject to NSR, while controlling for their characteristics, various sulfur dioxide regulations, characteristics of their locations and time trends. The analysis is aided by variation in NSR rules across boiler facility type and size, for instance through the fact that they did not apply to small boilers. We find that initial assignment to NSR grandfathering increases boiler utilization, survival and emission rates. On average, grandfathering is associated with around 787 additional hours under load annually, 2.05 pounds of additional sulfur dioxide emissions per MW of capacity per hour operated, and with a 1.5 percent

[4] New Source Review also regulated nitrogen oxides and particulate matter emissions from power plants. However, the compliance with these requirements was much cheaper than for sulfur—see, for instance (Linn, 2008) for the costs of nitrogen oxide abatement equipment—and so we can expect limited impacts from units being shielded from these requirements through grandfathering provisions.

[5] Compare, for example to greenhouse gases which have a global environmental impact through climate change.

increase in the probability of survival. We also show that in areas with stringent state sulfur dioxide regulations and in the so-called "non-attainment" areas, new source bias is reduced.

Our study is relevant for policy debates around the design of the Clean Air Act. When Congress enacted the modern version of the Clean Air Act in 1970 and when it amended it in 1977, adding the NSR provisions, the expectation was that most major stationary sources would quickly become subject to federal control despite the grandfathering provision. Lawmakers assumed units would be phased out over the course of their ordinary economic lives or upgraded, thereby, becoming subject to NSR.[6] However, the data suggests that over 40 percent of the coal boilers active in 1977 were still operational in 2018.[7]

Consequently, the possibility of new source bias in the context of NSR has garnered substantial attention over the last decades. The survival effects of grandfathering provisions have been of particular interest as some economists, legal scholars, and environmental groups have argued that NSR increased the lifespan of incumbent boilers (Ackerman et al., 1999; Hsu, 2006; Nash and Revesz, 2007; Revesz and Westfahl Kong, 2011; Schneider, 2001; Stavins and Gruenspecht, 2002). Clean Air Act court cases have also indicated that boiler lifespans have been prolonged beyond their normal economic life.[8]

Figure 3.1 plots boiler age at the observed time of retirement showing the much lower retirement age of boilers that have been subject to NSR throughout their entire in-service time—boilers that we refer to as "non-grandfathered." We think of boilers as "grandfathered" if for at least some part of their operations after the introduction of the 1977 CAA Amendments, they were not subject to NSR.[9] As for plants that are still in operation, a marked difference is also visible. In 2011, the

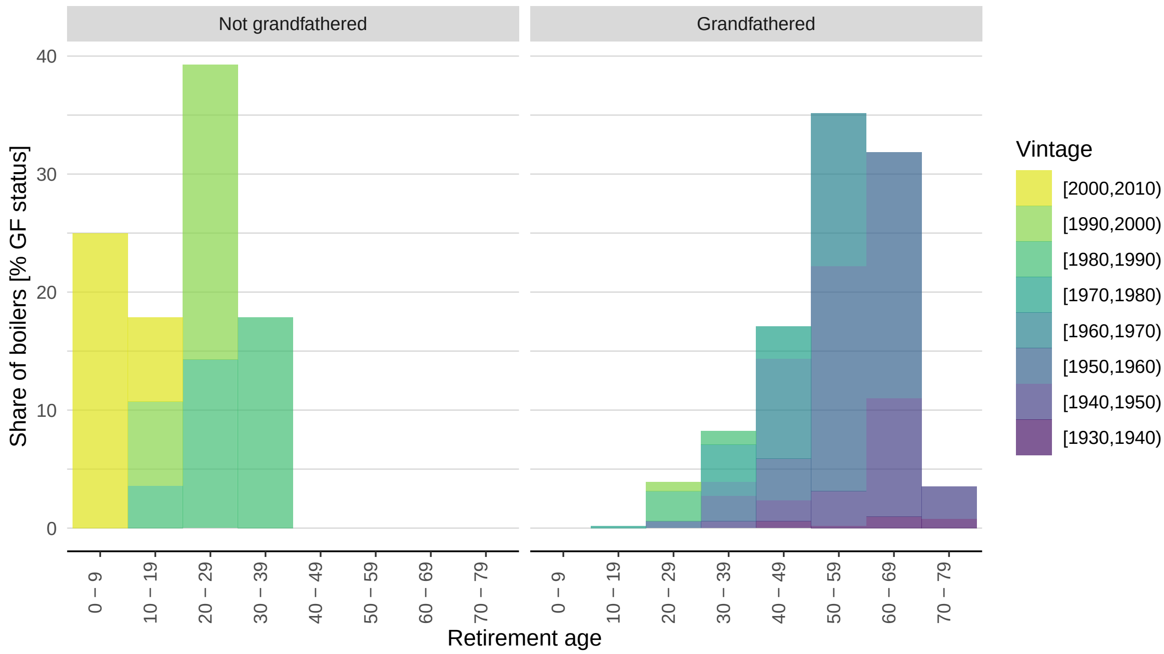
[6] Revesz and Lienke (2016) provide legislative records illustrating that expectation. For instance, during a hearing on NSR, Senator Howard Baker of Tennessee expressed the opinion that most of the 200 coal-fired power plants that were over twenty years of age at that time would be "phased out of operation in the next 5 to 20 years" (Revesz and Lienke, 2016, p. 48).

[7] The percent of coal boilers active across both 1977 and 2018 was estimated by combining information from Form EIA-767 with records from the PSC (2014).

[8] For instance, according to the documents from a court case filed against Duke Energy Corp., a company representative admitted that by the late 1980s, some of Duke's grandfathered plants had deteriorated to the point of being often or always out of service. Although normally the plants would have been scrapped, these plants were not retired. Instead, between 1988 and 2000, Duke replaced or redesigned boiler elements, even though the cost of replacing them was several times the original cost of the entire generating unit (Rabinowitsh, 2008).

[9] For the discussion of the chosen definition of grandfathering, see Section 3.3.6.

FIGURE 3.1. Boiler age distribution at retirement by NSR grandfathering status



Notes: Age distribution of boilers that retired between 1985 and 2017 for those that have been subject to NSR throughout their entire in-service time (i.e. "not grandfathered") and those which were not exposed to NSR for at least some of their in-service time (i.e. "grandfathered"). There are 508 and 29 observations in the grandfathered and not grandfathered groups, respectively.

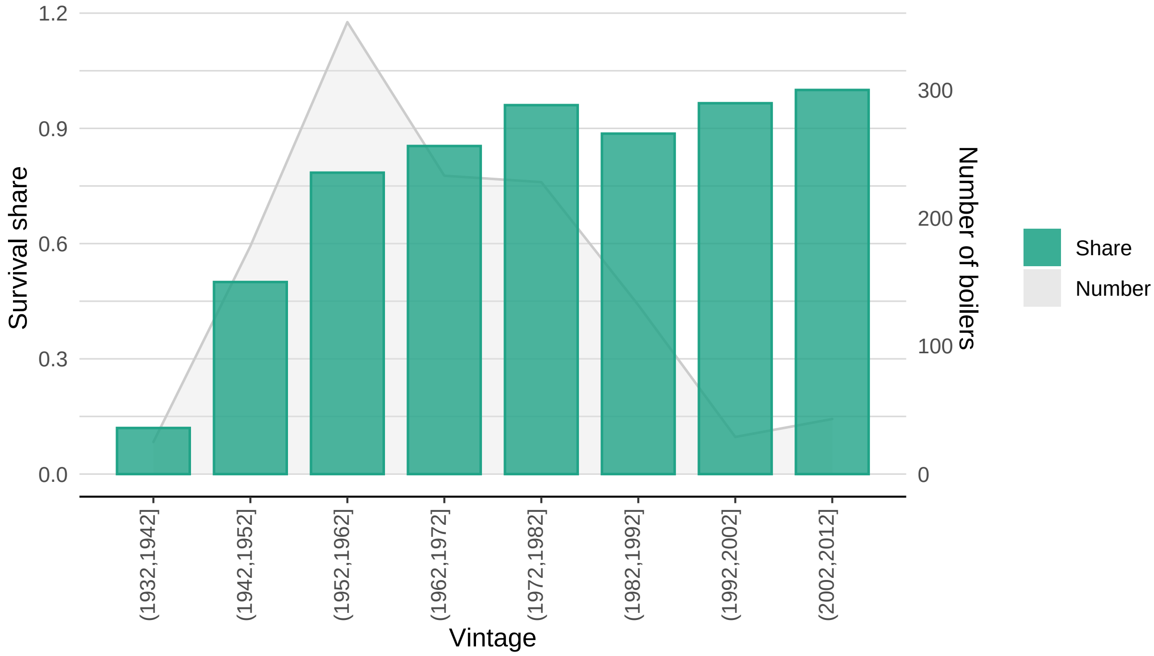
average age of a boiler subject to NSR was 31 years, while for those grandfathered, boilers were around 50 years.

The role of grandfathering in delaying boiler retirements could explain the slower than expected turnover in the boiler fleet. That said, alternative explanations are also possible. For example, it is conceivable that regulators were mistaken about the average lifespan of power plants or that their durability has improved over time.[10] Additionally, the interpretation of data like presented in Figure 3.1 is complicated by the fact that grandfathered boilers are necessarily older than non-grandfathered boilers.

Nevertheless, a naive analysis of the propensity to survive across boiler vintages is suggestive of a grandfathering effect. Figure 3.2 shows that the probability to survive up to year 2014 is monotonically increasing for boilers with vintages up to 1982, i.e., boilers largely under grandfathered

[10] Rode, Fischbeck and Páez (2017) point out that the lifespan of power plants has generally been increasing over time.

Figure 3.2. Propensity to survive until 2014 for boilers from different vintages



Notes: Boilers that retired before 1985 are not included.

status. However, for the 1983-1992 cohort for which the majority of boilers have been exposed to NSR since their inception, i.e., boilers that were not grandfathered, the probability to survive up to 2014 drops. For the 1993-2002 cohort where all boilers were subject to NSR, the likelihood of survival is only slightly higher than for boilers from the 1973-1982 period. Such non-monotonicity in the propensity to survive is counter-intuitive: one would expect the share of surviving boilers be higher for younger boilers, especially if the technology improves over time. It indicates that NSR grandfathering could have affected boiler retirements substantially. Establishing whether this pattern in survival rates is indeed driven by NSR grandfathering provisions requires a full-fledged empirical investigation. To the best of our knowledge, the implications of NSR grandfathering for boiler survival have not been studied empirically.

There exist studies, however, on closely related issues. Levinson (1999) looks at the effects of NSR grandfathering on the age of facilities in the commercial printing and paint manufacturing industries and finds no significant relationship. Heutel (2011) develops a structural model of boilers' scrapping, emissions and investment decisions. He uses the model to investigate how grandfathering provisions in New Source Performance Standards (NSPS)—a precursor to NSR, which could be met through low-sulfur coal without the need for pollution control equipment—affected boilers. Maloney and Brady (1988) and Nelson, Tietenberg and Donihue (1993) find a positive correlation between more stringent regulation—measured as expenditures of the state air quality management agency—and age of power plant capital. Both studies are frequently cited as support for the proposition that grandfathering delayed retirements.

Differences in emissions rates between new and grandfathered units have also garnered public scrutiny (Ackerman et al., 1999; Cohan and Douglass, 2011; GAO, 2012*a*), though only a few have attempted an empirical analysis. Apart from Heutel (2011), who focuses on emission effects of NSPS, the relevant studies include Nelson, Tietenberg and Donihue (1993) who find no correlation between emission rates and age of capital and Raff and Walter (2020) who find that non-attainment status can cause regulatory avoidance in grandfathered boilers through voluntary decreases in emissions. The impact of grandfathering on utilization, on the other hand, has largely escaped public attention with the exception of Stanton (1993), who finds a positive relationship between utilization and power plant NSR and NSPS status.

A response channel that has also attracted empirical investigation, but is beyond our scope, relates to potential adjustments in capital investments associated with the "modification rule"—an NSR sunsetting rule where significant modification of an existing unit exposes it to regulation. Bushnell and Wolfram (2012) documents distortions in capital investments by power plants driven by enforcement of the modification rule, while List, Millimet and McHone (2004) show how NSR distorted modification decisions in manufacturing plants.[11]

We contribute to the economic literature on the Clean Air Act by providing easily interpretable estimates of the utilization, survival and emissions rate associated with NSR grandfathering. Our results suggest substantial environmental harms due to NSR-exempt units. However, we also show that in regions with stringent local sulfur dioxide regulations, new source bias is reduced, emphasizing the complementarity between state and federal regulations. To our knowledge, our

[11] Other studies used changes in the modification rule's enforcement to estimate the value of grandfathering provisions for existing power plants (Lange and Linn, 2008) and to show how regulation on local emissions affects power plant carbon dioxide emissions (Chan and Zhou, 2021). Also, Keohane, Mansur and Voynov (2009) show that power plants decreased their emissions when it became likely they would be targeted by the Environmental Protection Agency in relation to the modification rule.

study represents the first empirical analysis that includes state-level sulfur dioxide regulations. This was made possible, in part, through the development a state regulation dataset with coverage from 1970 to the present. This novel contribution allows us to exploit variation in state regulations to more cleanly identify the effects of NSR grandfathering.

Finally, we contribute to the literature on the merits of vintage differentiation. Existing studies are mostly confined to theoretical analyses within the legal literature (e.g., Huber, 2011; Kaplow, 1986; Nash, 2009; Nash and Revesz, 2007; Revesz and Westfahl Kong, 2011; Serkin and Vandenbergh, 2018; Stavins, 2006). In economics, studies have noted how grandfathering can help solve commons problems (e.g., Anderson, Arnason and Libecap, 2011; Damon et al., 2019), and how grandfathering can be optimally used in the context of emissions trading (e.g., Böhringer and Lange, 2005; Hepburn, Quah and Ritz, 2007). Empirically, Coysh et al. (2020) find in a cross-country panel that greater vintage differentiation is associated with significantly higher retirement age, while Bialek and Weichenrieder (2021) report patterns in German foreign direct investment consistent with existence of substantial grandfathering effects.

The rest of the paper is structured as follows. Section 3.2 provides background information on sulfur emissions occurring as a byproduct of coal combustion, available emission reduction strategies, and various sulfur dioxide regulations in the US. Section 3.3 delineates the conceptual framework for our empirical investigation, while Section 3.4 provides an overview of the data. We present the estimation results in Section 3.5, while Section 3.6 concludes.

3.2. Background on sulfur abatement and regulations

3.2.1. Sulfur Abatement.

Burning coal is responsible for the majority of sulfur dioxide emissions.[12] The quantity of emissions produced through burning depends on abatement effort and coal sulfur content. The latter usually ranges between 0.5 and 5.0 percent, with the most sulfur-intensive coal sourced from the Appalachian and Illinois basins.

[12] In 1990, for instance, 70 percent of US sulfur dioxide emissions—around 16 million tons—were attributable to coal-fired generation (EPA, 2018).

To reduce the emissions intensity of sulfur dioxide, boiler owners rely on two main strategies: switching to less sulfur-intensive coal and installing sulfur-abatement equipment in the form of flue-gas desulfurization units. The latter, colloquially referred to as "scrubbers," remove sulfur dioxide from exhaust flue gases. Using low-sulfur coal can decrease emissions below 1.2 lbs of SO_2 per MMBtu, while scrubbers are capable of removing between 50 to 98 percent of the pollutant depending on the type of scrubber installed and its operation.

Low-sulfur coal tends to be more expensive than its high-sulfur counterpart as deposits of the former are less geographically convenient, resulting in higher average transportation costs. Scrubber installation, on the other hand, requires high investment, maintenance, and operation costs.[13] Moreover, flue-gas desulfurization equipment requires the use of corrosive chemicals and reagents which necessitate costly equipment maintenance and significantly shorten its lifespan (EIA, 2019).[14] Scrubbers also increase the fuel necessary to generate a unit of electricity, raising the heat rate of a coal-fired unit by around 2 percent (EPA, 2010).

The small, acidic particulates released as a result of burning coal can penetrate human lungs, such that even short-term exposures to airborne sulfur dioxide has been linked with asthma, bronchitis and other adverse health effects. With respect to the environmental effects, sulfur dioxide contributes to acidic deposition, constitutes a major precursor to particulate matter, and impairs visibility. These negative impacts drove a regulatory effort to curb sulfur dioxide emissions. Below, we outline the measures applicable to power plants. In the following Section, we discuss how we account for these measures in our analyses.

3.2.2. Federal regulations.

The first federal effort to control sulfur dioxide emissions from major power plants was undertaken within the framework of the Clean Air Act in 1971. It relied on emission intensity limits defined as

[13] According to estimates from the EPA, the initial capital cost of installing a wet scrubber was between $25 and $150 million for a 100 MW boiler, with an annual operating cost between $0.8 and $2.0 million (EPA, 2003). However, costs do not increase proportionally with the size of a boiler. A 650 MW boiler using a wet scrubber had capital costs between $65 and $162 million and an annual operating costs between $1.3 and $5.2 million (EPA, 2003).

[14] For such units, pollution control capital expenditures were estimated to account for around 20 to 27 percent of total capital costs, while annual pollution control expenditures account for about 23 to 31 percent of total annual generating costs (EPA, 2001).

part of the so-called New Source Performance Standards: boilers whose construction commenced after 1971 or were modified thereafter had to emit less that 1.2 lbs of SO_2 per MMBtu of heat generated by the combustion of coal.

The 1977 Clean Air Act Amendments proposed a stricter set of rules for larger facilities, known as New Source Review. NSR required that the construction of a new facility or the expansion of an existing one was subject to a permitting process. The permit application process is very complex and can involve up to five different stages: permit preparation, determination of application "completeness," public notice and comments, iterative responses to comments, and possible administrative and judicial appeals (Fraas, Neuner and Vail, 2015). The process can be costly due to the large investment of time and resources, the associated uncertainties, and possible delays (Fraas, Neuner and Vail, 2015).[15]

Under NSR, facilities located in non-attainment areas—counties containing pollutant concentrations above threshold levels defined by the National Ambient Air Quality Standards (NAAQS)—must meet additional requirements. In order to gain a permit to build or modify a plant, facilities must generally obtain offsets for the resultant increase in emissions (Shapiro and Walker, 2020). These permits, depending on the region, can be very expensive.[16] Importantly, states are also required to make "reasonable further progress" on improving the air quality in their non-attainment areas, which leads to additional state-level regulation beyond the federal requirements. Meanwhile, facilities in attainment areas are instead subject to the "Prevention of Significant Deterioration" permitting process. It is more lenient as it does not require offsetting, and states are mandated only to avoid substantial degradation of air quality (Nash and Revesz, 2007).

NSR also imposed very stringent sulfur dioxide emission reductions: most boilers with capacity above 73 MW that generate electricity for utility sales faced a mandatory 90 percent emissions abatement, irrespective of the state attainment status.[17] In 1984, the same permitting and abatement regulations were introduced for new or modified commercial and industrial boilers above 10

[15] Between 2002 and 2014, the permitting process for new coal boilers took, on average, 496 days or over 16 months (Fraas, Neuner and Vail, 2015).

[16] EPA (2001) quotes the price range for 2001 sulfur dioxide offsets as between \$6,000 to \$7,667 per ton per year.

[17] If a boiler's sulfur dioxide emissions are below 0.60 lbs of SO_2 per MMBtu, the boiler is only required to reduce input sulfur dioxide emissions by 70% compared to its potential emissions. Regulated boilers are defined as these that are constructed for the purpose of supplying more than one-third of their potential electric output capacity to a utility power distribution system for sale.

MW. Then in 1989, these were further extended to new and modified commercial and industrial boilers with capacity above 1 MW. The culmination of these NSR requirements effectively required the installation of scrubbers.

The 1990 Clean Air Act Amendments, known as the Acid Rain Program, maintained NSR requirements but added the obligation to participate in a sulfur dioxide cap-and-trade program. In the first phase, between 1995 and 2000, only the largest boilers were required to participate. Afterwards, compliance was mandatory for all boilers with a capacity above above 25 MW. The permit prices per ton of emissions fluctuated between $0.01 and $860. In 2009, the Clean Air Interstate Rule became effective. For boilers located in upwind states, the new obligations introduced by the Rule were tantamount to doubling compliance costs by requiring two Acid Rain Program permits for each ton of emitted sulfur dioxide.[18]

The Cross-State Air Pollution Rule replaced the Clean Air Interstate Rule in January 2015. This resulted in the introduction of local, sulfur dioxide emission trading programs. In the first phase, trades occurred separately for the so-called Group 1 and Group 2 states, which roughly correspond to upwind and downwind states, respectively. In the second phase of the program, starting in 2017, sulfur dioxide budgets were substantially tightened and additional trade restrictions between states were imposed. However, the emissions budgets under the Cross-State Air Pollution Rule were lenient. In most of the Group 1 states, for instance, the actual emissions in 2015 were already lower than the emission budgets for the second phase (Fotouhi, Dunn and Crutcher LLP, 2016). Consequently, emission allowances were available at relatively low prices between $1 to $5 per permit.

[18] The Acid Rain Program allocated some sulfur dioxide permits for free to incumbent power plants, i.e. some permits were grandfathered. However, due to the design of the allocation process and the permits' inherent opportunity costs, the grandfathering policy likely did not affect boiler operations or retirement decisions. As Burtraw and Szambelan (2009) note, the law distributed emissions allowances to each affected unit on the basis of its heat input during a historical base period—from 1985 to 1987—multiplied by an emissions rate and adjusted to make aggregated emissions equal the target emissions cap. Only plants in existence over the base period received an allocation, and their owners continued to receive it even after retirement.

3.2.3. State regulations.

States in which NAAQS are violated are required to develop a regulatory plan setting out a trajectory to meet air quality standards within each county. These plans create a separate layer of sulfur regulation, complementing federal standards. States tended to develop regulations for coal boilers either through a performance standard of sulfur dioxide emissions per MMBtu or through limiting the sulfur content of combusted coal. In a given state, regulatory stringency may depend not only on the vintage of the boiler, but also on its size, number of stacks, location, etc., with some states regulating individual counties separately. Generally, though, state regulations are more lenient than NSR requirements. Consequently, for boilers already subject to NSR, state regulations rarely cause additional compliance costs. However, in some states, regulations may cause high compliance costs for facilities grandfathered from NSR, creating variation in compliance costs across boilers.

3.3. Conceptual framework

In this section, we discuss our empirical approach. We are interested in the effects of NSR grandfathering provisions on the margins of coal boiler operations: the intensive margin as captured through utilization and emissions; and, the extensive margin as represented by boiler survival. We first discuss the theoretical foundations for these relationships and then present the functional form of our empirical specification. Since it forms such a large part of our identification strategy, we also outline our approach to each potentially confounding environmental regulation in detail. Finally, we discuss the possible threats to a causal interpretation of our results.

3.3.1. Utilization effects.

The main channel through which NSR grandfathering affects boiler utilization is the additional generation costs imposed on regulated units through the *de facto* scrubber requirement. Scrubbers have high operations and maintenance costs, entail frequent equipment replacements, and reduce boiler efficiency.[19] Furthermore, in non-attainment regions, new and modified units must obtain offsets for any net increase in emissions (Shapiro and Walker, 2020).

Ceteris paribus, NSR grandfathering provisions, thus, provide a substantial variable cost advantage, which should translate to higher utilization rates. Under cost minimization, boilers with lower marginal costs should be dispatched more frequently both in wholesale market settings and in the context of regulated, vertically integrated utilities. The difference in the number of hours under load between grandfathered and non-grandfathered boilers should be indicative of this cost advantage.

Marginal costs are, however, only one potential driver of utilization. The number of hours a boiler operates in a year will also be a function of market conditions—including load duration curves—market structure, and market conduct. All else being equal, more frequent high demand occurrences should result in higher boiler utilization. Market structure relates to the costs and capacities of other units serving load in the given location, as well as their ownership structure. Market conduct is defined by the level of competition and the exercise of any underlying market power.

As we do not observe the load shape, competition structure or the costs and capacities of the rival generation fleet, we rely on the assumption that there are no systematic differences between the demand and competition faced by grandfathered and non-grandfathered boilers. A potential issue here is that both market structure and conduct are related to the electricity regime, and many regions in the US underwent restructuring from vertically-integrated monopolies to liberalized markets during the analyzed time horizon (Borenstein and Bushnell, 2015). There exists evidence suggesting that this problem may not be very pertinent to our study, though some recent work suggests the opposite.[20] For our approach, we require that market restructuring affected grandfathered and non-grandfathered boilers symmetrically.

[19] See Section 3.2 for further details.

[20] Douglas (2006) shows that the effects of liberalization on coal boilers' utilization were modest and limited to a few regions. On the other hand, Knittel, Metaxoglou and Trindade (2019) find that generators behaved differently in restructured markets in response to changes in gas prices.

With utilization driven by cost minimization considerations, we define the following function to explain the number of hours boiler i runs in year t:[21]

$$hours_{it} = f\left(GF_{it},\ \boldsymbol{\Omega}_{it};\ \mathbf{X}^H_{it},\ \mathbf{Z}^H_{jt},\ \alpha_j,\ \mu_m,\ \eta_t\right) \tag{3.1}$$

where indices m and j represent boiler owner type and its location, respectively. Here, grandfathering status, GF_{it}, is our variable of interest, while $\boldsymbol{\Omega}_{it}$ are applicable environmental regulations as discussed in more detail in Subsection 3.3.5. Boiler-level characteristics, such as age and capacity, are included in the term $\mathbf{X}^H_{it}$, while $\mathbf{Z}^H_{jt}$ defines location-specific characteristics. Depending on the specification, these may include utility or state demand, state generation capacity, etc. We also allow the location, owner type and year to directly affect the boiler utilization through terms α_j, μ_m and η_t, respectively.

A significant and positive coefficient on grandfathering status would indicate a marginal cost advantage associated with NSR exemption but would not explain the mechanism through which that advantage occurs. With our data, though, we can study auxiliary plant loads through the net-to-gross generation ratio, i.e. net generation measured at the power plant's connection to the grid over gross generation measured near the generator. The ratio is relevant for our analysis as the amount of electrical power required to operate a scrubber represents an auxiliary load. We would thus expect boilers operating scrubbers to have less electricity available for export to the grid, which is equivalent to a lower net-to-gross generation ratio, all else being equal. Consequently, systematic differences in generation ratios between grandfathered and non-grandfathered boilers could be indicative of the electricity expense associated with scrubber operations driven by NSR.

To explore generation ratios, we perform the following naive regression using weighted least squares:

$$GR_{it} = \alpha + \beta GF_i + \mathbf{X}_{it}\boldsymbol{\gamma} + \varepsilon_{it} \tag{3.2}$$

where GR_{it} is the net-to-gross generation ratio for boiler i during month t. We weight the regression using monthly hours under load. The set of covariates, $\mathbf{X}_i$, represent various boiler characteristics, including age and size. Finally, α is the intercept, while the ε_{it} term represents robust standard errors.

[21] We define utilization as hours under load, that is the number of hours a unit operates.

3.3.2. Survival effects.

We now turn to the mechanisms through which NSR grandfathering affects boiler survival. Specifically, we want to understand the relationship between NSR grandfathering and the turnover of the coal-fired fleet. Where utilization depends primarily on operations, survival depends on both operations and capital expenditures. As elaborated above, grandfathered plants tend to have an advantage in short-run variable costs. This advantage also extends to long-term fixed costs.

Coal-fired power plants under an NSR obligation had limited options for compliance. Given the stringency of the regulation, owners were effectively obliged to install and run a scrubber, adding substantial investment, maintenance and generation costs. [22] These additional costs were largely avoided by grandfathered plants, even if they were subject to state regulations. Since local environmental requirements tend to be less onerous than those under NSR, they usually offer a wider array of feasible compliance strategies, including switching to low-sulfur coal.

To understand how this cost advantage could affect the survival of grandfathered boilers, we build a framework that reflects the retirement decision faced by boiler owners. In most cases, a boiler will be retired if the cost of its continued operation is sufficiently higher than that of its replacement such that the lower operational costs outweigh the capital costs of demolishing and replacing the existing boiler. Assuming a replacement boiler is identical in size, location and fuel source, the retirement decision at time t for boiler i in location j made by owner type m depends on the comparison of the following values:

$$\pi_{it}^{E} = R_{it}^{E} - C^{E}\left(GF_{it},\ \mathbf{\Omega}_{it},\ size_i,\ \mathbf{X}_{it}^{S},\ \mathbf{Z}_{jt}^{S},\ \mu_m\right) \tag{3.3}$$

$$\pi_{it}^{R} = R_{it}^{R} - C^{R}\left(\mathbf{\Omega}_{it},\ size_i,\ \mathbf{Z}_{jt}^{S},\ \mu_m\right) - \kappa_t\left(\mathbf{\Omega}_{it},\ size_i,\ \mu_m\right) - S_{ijmt}, \tag{3.4}$$

where π_{it}^{E} represents profits associated with the continued operation of the existing boiler and π_{it}^{R} is the profit associated with replacement. The operating costs for an existing boiler, $C^{E}(\cdot)$, depend on its pollution control equipment, which is driven by: its grandfathering status, GF_{it}; its generation capacity, $size_i$; and, the remaining characteristics of the boiler, $\mathbf{X}_{it}^{S}$, including age. These costs are also influenced by environmental regulations applicable to the specific boiler, $\mathbf{\Omega}_{it}$,

[22] These costs are described further in Subsection 3.2.

where grandfathering status may attenuate some of their effects. Local cost determinants, such as regional demand and competitive pressure but also location-level fixed effects, are captured by $\mathbf{Z}^S_{jt}$, while μ_m captures the costs specific to the owner type. The operating costs for a new unit are given by $C^R(\cdot)$ and its investment cost, $\kappa_t(\cdot)$, can differ over time. Changes in operation costs associated with boiler replacement affect the amount of electricity generated and revenue, $R(\cdot)$, such that $R^R_{it} = R^E_{it} + \psi\left(C^R(\cdot) - C^E(\cdot)\right)$. Finally, $S_{ij}(\cdot) = S + e_{it}$ captures the scrappage costs for boiler i. If the difference between Equations (3.4) and (3.3) is positive, the boiler gets replaced, such that the survival of the boiler can be represented by:

$$survive_{it} = g\left(GF_{it},\ \mathbf{\Omega}_{it};\ size_i,\ \mathbf{X}^S_{it},\ \mathbf{Z}^S_{jt},\ \alpha_j,\ \mu_m,\ \eta_t\right) \tag{3.5}$$

We do not separately model upgrade decisions for existing units, e.g. turbine upgrades or condenser optimization. Instead, we assume that the profits of an existing plant are based off an optimal upgrades plan and that the possibility of improvement is not limited by grandfathering status. In other words, we assume that the NSR modification rule did not affect behavior and boiler profits. This is motivated by the fact that for much of our sample period, the modification rule was lightly enforced.[23] Finally, similar to utilization, we ignore potential market effects. The framework presented in Equation (3.5) does not capture the effect that boiler replacement has on other operating units.

3.3.3. Emission effects.

As boilers regulated by NSR face stricter sulfur regulations, we can expect their emission rates—the amount of emissions released per unit of generation—to be lower than those for grandfathered units. This does not imply, however, that grandfathered units went unregulated. Boilers built before 1978 may be exempt from NSR but still subject to an earlier New Source Performance Standard or state regulation, which could create incentives for using low-sulfur coal and, in some cases, even to

[23] The effects of the modification provision could be proxied within our framework, for instance by interacting the age of boilers with grandfathering status. However, this relationship would need to be time dependent as the enforcement of the provision changed over time. See Lange and Linn (2008) and EELP Regulatory Tracker New Source Review.

install scrubbers. In addition, the 1990 Clean Air Act Amendments launched a sulfur dioxide cap-and-trade market, which made it economically desirable for coal plants to take available low-cost steps to reduce their sulfur emissions. And indeed, over time, many grandfathered boilers found it profitable to use low-sulfur coal or install scrubbers.

To study the difference in emissions associated with NSR grandfathering, we assume the average emissions rate of boiler i in year t can be represented by the the following function:

$$emissions_{it} = h\left(GF_{it},\ \boldsymbol{\Omega}_{it};\ \mathbf{X}^E_{it},\ \mathbf{Z}^E_{jt},\ \alpha_j,\ \mu_m,\ \eta_t\right), \tag{3.6}$$

with $\mathbf{X}^E_{it}$ and $\mathbf{Z}^E_{jt}$ being the relevant boiler- and location-level characteristics. All other variables are defined equivalently above.

3.3.4. Environmental regulations.

We are interested in the effects of NSR grandfathering provisions on operations, survival, and emissions. Nevertheless, our regressions must also account for other sulfur dioxide regulations described in Section 3.2 as they could otherwise pollute the inference. In the above subsections, we left unspecified, how environmental policies, $\boldsymbol{\Omega}_{it}$, are modeled in Equations (3.1), (3.5), and (3.6) and how they interact with grandfathering status, GF_{it}. Below, we provide the empirical implementation details for the relevant programs.

New Source Review.

NSR greatly raised the fixed and variable costs faced by boilers through a complex permitting process and abatement requirements for sulfur dioxide emissions. As there is no indication that the NSR compliance costs have substantially changed over time, we model the NSR status of the boiler through an indicator variable, GF_{it}, which equals one for grandfathered boilers and zero otherwise. As the fixed and variable costs of scrubbers vary with boiler size, we adopt interactions between grandfathering and boiler capacity, $GF_{it} \cdot size_i$.

National Ambient Air Quality Standards.

NSR prescribes additional obligations for units located in non-attainment areas, as classified according to NAAQS. Consequently, the competitive advantage from NSR grandfathering may depend on the attainment status of its county. We model this through an indicator variable for non-attainment status, $NAAQS_{jt}$, and an interaction term with grandfathering status, $GF_{it} \cdot NAAQS_{jt}$.

New Source Performance Standards and state regulations.

New Source Performance Standards and state regulations effectively limit the amount of sulfur dioxide that regulated boilers can emit per MMBtu. As a consequence, if a unit is subject to both NSPS and state regulations only the more stringent is binding. We, thus, capture these two regulatory regimes through one continuous variable, $MMBTU_{it}$, which we construct as the inverse of the more stringent standard.[24]

Sulfur cap-and-trade programs.

Notwithstanding their NSR status, boilers could face participation obligations for the sulfur dioxide cap-and-trade programs: the Acid Rain Program, the Clean Air Interstate Rule, and the the Cross-State Air Pollution Rule. We expect these programs to affect boilers through their price on emissions. We, thus, control for boiler-specific cap-and-trade emission prices, $price_{it}$. The absence of permit requirements is modeled as $price_{it} = 0$.[25] However, the effect of permit requirements may differ across boilers. Those capable of emitting relatively little pollution should be less responsive to permit prices. The level of emissions is in turn largely driven by the sulfur content of utilized coal. We, therefore, allow for heterogeneous price effects by interacting permit prices with a variable capturing coal sulfur content, $price_{it} \cdot SO2cont_{it}$.

Unfortunately, sulfur content is endogenous. This is most evident in the context of the survival analysis. Given an inefficient boiler with a high likelihood of retirement, an owner likely wishes to avoid the high fixed costs of scrubber installation and, thus, is more likely to reduce the sulfur

[24] If the unit is not regulated, we code it as facing a limit of 10 lbs of SO_2 per MMBtu—a standard far in excess of typical boiler operations. In constructing of the variable, our inversion of the limit helps reduce the potential effect of the choice of the "never binding" limit could have on the results.

[25] As the permit prices for the Cross-State Air Pollution Rule have been negligible, while the program participation rules are highly complex, we assume the permit prices for that program to equal zero.

content of the combusted coal when facing high emission permit prices. In contrast, an owner of a highly efficient boiler may find scrubber installation optimal. To deal with the arising endogeneity problem, we take advantage of the fact that the relative profitability of these two strategies depends on the geographical location of the plant. As coal transport is expensive where its cost can exceed those of the commodity itself, we expect the proximity of low-sulfur coal reserves to lead to lower average sulfur content. Hence, we instrument for the sulfur content variable using the mean sulfur content of close-proximity coal, $SO2contIV_i$.[26]

3.3.5. Empirical specification.

Below, we present the functional form for our empirical specification. Given the relationships outlined above along with the description of the various sulfur dioxide regulatory programs, we apply a similar linear model for each outcome variable, y_{it}: utilization, survival and emissions. We estimate the following regression for boiler i and owner type m located in region j during year t:

$$\begin{aligned} y_{it} = & \beta_1 GF_{it} + \beta_2 NAAQS_{jt} + \beta_3 NAAQS_{jt} \cdot GF_{it} \\ & + \beta_4 MMBTU_{it} + \beta_5 MMBTU_{it} \cdot GF_{it} \\ & + \beta_6 price_{it} + \beta_7 \widehat{SO2cont}_{it} + \beta_8 price_{it} \cdot \widehat{SO2cont}_{it} \\ & + \mathbf{X}_{it}^{y} \mathbf{\Gamma}_{x}^{y} + \mathbf{Z}_{jt}^{y} \mathbf{\Gamma}_{z}^{y} + \alpha_j + \mu_m + \eta_t + \varepsilon_{it}, \end{aligned} \tag{3.7}$$

where $\widehat{SO2cont}$ is the instrumented variable capturing coal sulfur content; $\mathbf{X}_{it}^{y}$ and $\mathbf{Z}_{jt}^{y}$ are the sets of boiler-specific and location-specific explanatory variables relevant for outcome variable y; and, ε_{it} is an i.i.d. error term.

Our variable of interest is the NSR grandfathering indicator GF_{it}. Assuming our framework captures the causal effects of grandfathering, its coefficient β_1 is interpreted as the direct effect of grandfathering status on the particular outcome variable for boilers located in attainment areas that do not face additional requirements through New Source Performance Standards or state regulations.[27] However, an indirect effect of grandfathering may also exist. As illustrated in

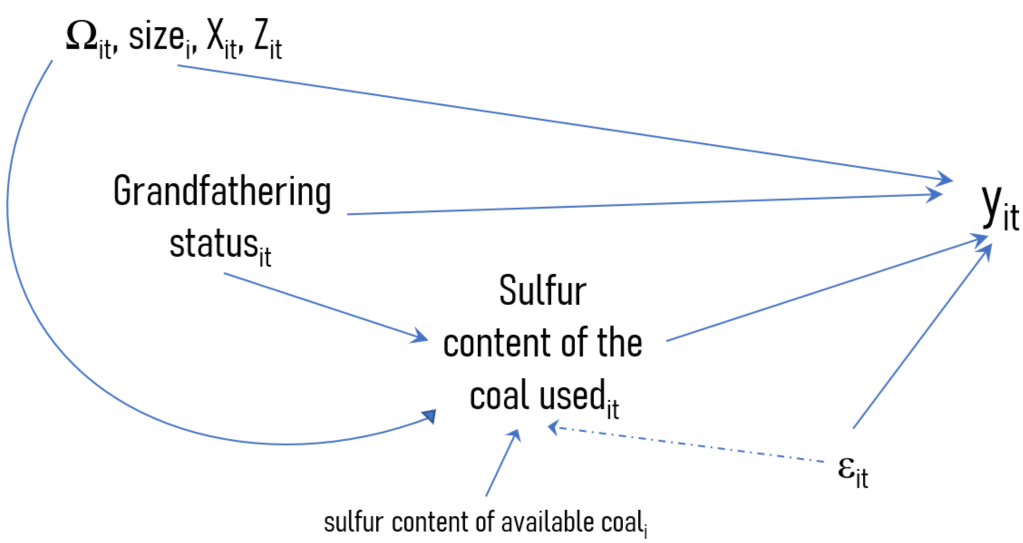
[26] For further details on the construction of the close-proximity coal instrument, see Section 3.4.3.
[27] For a discussion on the appropriateness of the causal interpretation of coefficients, see Subsection 3.3.6.

Figure 3.1, grandfathering influences the choice of coal sulfur content,[28] which itself affects the outcome variables and thus acts as a mediator. Hence, sulfur content is a function of grandfathering. To compute the total effect of grandfathering on boilers located in attainment areas that do not face additional requirements through NSPS or local regulations, we must sum the direct and indirect effects by taking the partial derivative with respect to grandfathering:

$$\frac{\partial y_{it}}{\partial GF_{it}} = \beta_1 + (\beta_7 + \beta_8 price_{it}) \cdot \frac{\partial SO2cont_{it}}{\partial GF_{it}}. \tag{3.8}$$

For boilers located in non-attainment areas or subject to other sulfur regulations, Equation (3.8) must also include the terms $\beta_3 NAAQS$ and $\beta_5 MMBTU_{it}$, respectively.

FIGURE 3.1. Direct and indirect effect of grandfathering.



Notes: Graphical representation of the causal relationships between variables and the endogeneity of the sulfur content of the coal used. Weighted sulfur content of the available coal is used as an instrument.

The remainder of the covariates with β coefficients are sulfur regulations as described in Subsection 3.3.4. Boiler-level characteristics—age, capacity and the instrumented sulfur content of utilized coal—are included in the vector $\mathbf{X}_{it}$. The vector $\mathbf{Z}_{jt}$ represents the characteristics of location j.

[28] By imposing a very strict scrubber requirement, NSR partly removes the incentive to use low sulfur coal for compliance with other sulfur programs.

The variables included here depend on the specification. For utilization and survival regressions, we allow state-level load growth to enter the estimations. The intuition is that with increasing electricity demand more units need to be online at the same time, and in the long-run, participants may decide to expand generation capacity. An investment in new capacity may not preclude keeping existing boilers operational, even if they are expensive compared to a new unit. We also include measures of competitive pressure for our survival and utilization regressions, including: generation capacity growth at the state-level and coal-gas price ratios.

There may also be differences in decision-making between owner types. For instance, state-regulated investor-owned utilities usually face cost of service regulation under which they are allowed to recover prudently incurred costs plus a rate of return on capital expenditures. While potential overspending on capital investments is monitored by regulators, the incentives for boiler replacement may be somewhat different for investor-owned utilities than for co-ops or industrial owners. For independent power producers, on the other hand, the retirement decisions may not lead to replacing the unit but instead with ceasing operations altogether. For the decision about how frequently to run a boiler, on the other hand, the utilization of industrial boilers can be coupled with working times of the facilities, while for independent power producers it may depend more on the cost structure of competitors. To control for potential heterogeneity, we use owner type fixed effects in the regressions, μ_m. Thereby, we differentiate between independent power producers, investor-owned utilities, industrial facilities, etc. In some specifications, we interact the owner-type fixed effects with grandfathering status.

Time fixed effects, η_t, control for changes in other policies and market-level changes, such as investment costs of alternative technologies. We account for time-invariant local characteristics using state-level fixed effects, α_j. Finally, by imposing that the term ε_{it} is i.i.d., we can estimate Equation (3.7) using OLS.

3.3.6. Causal interpretation of the results.

There are two main threats to causal interpretation of the β parameters: potential endogeneity of grandfathering status and systematic differences between grandfathered and non-grandfathered units.

First, thresholds in regulations always raise concerns about bunching behavior. In our setting, this would mean boiler owners manipulating their construction commencement date in order to gain grandfathering status. However, the grandfathering cutoff date was coincident with the establishment of the regulation, leaving little chance for manipulation post-announcement. There still exists the possibility of boiler owners anticipating the regulation along with the grandfathering provisions and manipulating their construction date. While theoretically possible, it is rather unlikely given the long lead times that coal boilers require. This is due to their substantial capital requirements and extensive regulatory approvals process, which limits the opportunity to accelerate construction decisions. Unfortunately, we are unable confirm the absence of construction manipulation empirically as we lack comprehensive data on commencement dates.

However, grandfathering status could also be endogenous due to the NSR modification rule. The rule stipulates that boilers lose their grandfathering status if they undergo substantial modifications. Under such conditions, only boilers that gain the most from upgrades perform them and lose their grandfathering status. These are likely the most valuable boilers with a long expected lifespan and for which the upgrade significantly improves its efficiency. Conversely, for a boiler approaching the end of its useful life given its technical state, performing an upgrade that exposes it to NSR may not be profitable.

For the majority of our sample period, the modification rule was weakly enforced. This implies that upgrades are unlikely to introduce bias into our regressions. However, in later periods, boilers performing significant upgrades were exposed to NSR (Bushnell and Wolfram, 2012; Lange and Linn, 2008). This was especially true during the Clinton and Obama administrations, such that in later years we expect a correlation between grandfathering status and unobserved variables determining boiler survival and operations. We address this selection issue by disregarding changes in grandfathering status and, instead, adopt the initial assignment to grandfathering.

That is, we define grandfathering as the status the unit had at the inception of NSR or when the unit commenced operation. Consequently, we estimate the impact of initial assignment to later survival, utilization, and emissions. This is equivalent to dropping the t subscript on our grandfathering indicator.

Unfortunately, this modeling choice compounds the second problem we face: the possibility that grandfathered and non-grandfathered units are systematically different. By design, only the older boilers received grandfathering status.
footnote Older boilers refers to those whose construction commenced before September 1978 when serving utilities, before 1986 when serving commercial and industrial owners, and before 1989 for small commercial and industrial boilers. The oldest exempted coal-fired boiler commenced operations in 1926. This results in the two groups—grandfathered boilers and these subject to NSR—differing in terms of age and underlying technology. That is, if boilers became more efficient over time, our estimates will be biased downwards and the finding of a significant effect is at worst understated.

This problem is partly mitigated by the varying applicability of NSR across boilers of different size and type. We also attempt to control for the heterogeneity between groups by using various boiler-level controls. These can capture such differences as age and boiler size but will not reflect all possible technological change over time. As the efficiency of coal boilers improved over time (Rode, Fischbeck and Páez, 2017), we can expect our estimates of the effect of grandfathering on survival to be biased downwards. In one of the robustness checks we limit our sample to boilers with in-service years between 1975 and 1988, leading to higher overlapping support between the two groups.[29] This technique is appropriate for utilization and emissions regressions, where there is sufficient variation in the outcome variables. Unfortunately for survival, too few boilers from that vintage have retired, such that we cannot restrict our sample to these units only.

[29] During the eighties, we also observe both grandfathered and non-grandfathered units commencing service concurrently, further increasing the similarity of grandfathered and non/grandfathered boilers. See Section 3.4.1 for a detailed explanation of which boilers were exempted from NSR.

We synthesize a variety of electricity and regulatory data in order to assess the effect of NSR grandfathering. Below, we discuss the sourcing and preparation for federal and local regulations, boiler characteristics and operations, and electricity markets. Table 3.A.1 in Appendix 3.A summarizes our dataset.

3.4.1. Federal regulations.

This section discusses data related to federal sulfur dioxide regulations. We commence with a description of NSR grandfathering status and then move on to other federal regulations below.

Accurate assignment of grandfathering status to coal-fired boilers is crucial for our analysis. However, datasets with comprehensive regulatory status information do not exist, making it difficult to ascertain which units have obtained NSR permits.[30] Two sources—the Environmental Protection Agency (EPA) and the Energy Information Administration (EIA)—provide some information that is indicative of grandfathering status. However, their records are inconsistent and incomplete, and it is challenging to establish which units were exempted from NSR at which time.[31]

To address the problem, we return to the date defined in the regulation as a cutoff for grandfathering: for boilers generating electricity for utility sales, construction must have commenced prior to September 18, 1978.[32] We first identify boilers around the cutoff using in-service data from the EIA-767. We also assume that all boilers, apart from those classified as commercial or industrial in the EIA-860, generate electricity for utility sales. While this assumption surely holds for boilers belonging to investor owned utilities, it may be inconsistent for other boiler types—including those classified as "state" or "federal"— which we would unintentionally misassign grandfathering status.

[30] This is a known problem acknowledged by the Government Accountability Office (GAO, 2012*b*).

[31] The EPA gathers relevant permit information in the "RACT/BACT/LAER Clearinghouse" which had been used in earlier studies for the identification of grandfathered boilers. However, the Clearinghouse data suffers from a number of drawbacks. It is a voluntary dataset across many regulatory programs. Thus, it does not incorporate all NSR permits and includes many which are unrelated to NSR entirely. Furthermore, the dataset lacks unique identifiers making it challenging to extract relevant permits. The EIA-767, on the other hand, releases data on applicable regulations and NSR permits that could be used to establish grandfathering status. Unfortunately, the data is inconsistent and, frequently, implausible.

[32] See 33580 Federal Register 44, No. 113 (11 June 1979).

Given relatively long construction times for larger coal boilers, we assume that all boilers generating electricity for utility sales whose service began before 1981, had commenced construction prior to September 1978. Thus, such boilers were not exposed to NSR when the rules were introduced. For boilers whose operations began after 1988, we assume their construction started after 1978 and, thus, were subject to NSR. For all remaining boilers generating electricity for utility sales, we manually gather information on their construction commencement date. This included inquiries with state environmental departments and, in some cases, directly contacting individual power plants. For the 104 commercial and industrial boilers in our dataset, we assume they were grandfathered if: (1) they began service prior to 1987 and had a capacity above 10 MW; (2) they began service before 1991 and had a capacity between 1 and 10 MW; or (3) they have a capacity below 1MW. We believe that through this approach, we can correctly assign the grandfathering status to the majority of boilers. However, given variations in construction time and the potential errors in the responses to our individual inquiries, we expect some misassingment of grandfathering status for boilers taken into service in the years immediately following the passage of NSR.

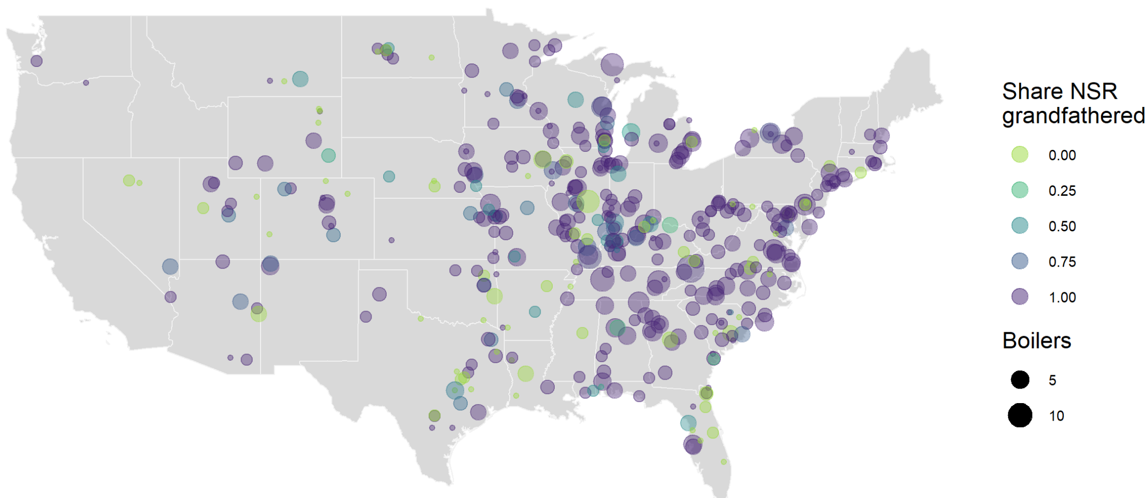
Figure 3.1 presents the final set of boilers along with their grandfathering status.

Regarding other federal regulations, we mark boilers as grandfathered from New Source Performance Standards if they commenced operations prior to 1973 and self-reported as exempt in EIA-767. For the Acid Rain Program, we first establish whether a boiler was subject to its first phase by checking whether it was included in Table 1, Subpart B of the Clean Air Act Amendments 1990 regulations. For the second phase, we assume all boilers with capacity greater than 25 MW are program participants. We source permit prices from spot auction data published by the EPA. Finally, information on county attainment status stems from the EPA Green Book and, for years before 1991, from work by Randy A. Becker as made available by the EPA.

3.4.2. State regulations.

We build a state-level regulatory dataset through a comparison of: EPA summary files from the 1970s on sulfur dioxide regulations for coal-fired power plants; archived state administrative codes

Figure 3.1. Coal-fired boilers by initial NSR grandfathering status



Notes: Initial grandfathering status refers to the original assignment of NSR grandfathering status. Bubbles show individual power plants, while their size represents the number of constituent coal-fired boilers. The color indicates the share of boilers within each power plant which are NSR grandfathered. Due to data limitations, we exclude California, Maine, Ohio and Pennsylvania.

from the 2000s; and, current state administrative codes.[33] If the three sources were consistent, we assume the same set of standards applied throughout our sample period. If there were differences, we undertook an investigation to pinpoint when and how many times the standards changed.[34]

The investigation was highly idiosyncratic and dependent on the particular sources available for each state. For example, we consulted: two EPA reports compiling all state sulfur performance standards, one from 1975 and one from 1976; State Implementation Plan revision histories available through the Federal Register; old versions of state administrative codes available online; and, in some cases, EPA documents describing the effective dates of different provisions in the State Implementation Plans. The stringency of the local regulations frequently depends on plant

[33] The EPA summary files reviewing sub-national sulfur dioxide regulations were published in March 1976 and September 1977.

[34] We exclude California and Ohio due to the complexity of their regulations, as well as Maine and Pennsylvania since the geographic boundaries of their air quality control regions (AQCR) are not county-defined. Both cases render a clean assignment of regulatory regime to power plant a time-intensive and impractical exercise. In fact, clean assignment may not be possible in some cases. A handful of other individual observations from other states were removed for similar reasons.

characteristics, such as capacity, location, vintage, etc. In some cases, individual boilers or plants were singled out for regulation. We, thus, account for boiler characteristics when matching them with the local regulations. These standards were often emissions standards based on pounds of sulfur dioxide per MMBtu. Other times, they were fuel composition requirements.[35] Occasionally, they were limits on parts of sulfur per million. Sometimes the standards were also tied to stack height. Consequently, it was not always possible to parse the standards into equivalent values.[36] Figure 3.C.1 in Appendix 3.C presents the mean local regulation by state as defined by our research.

3.4.3. Boiler technical data.

We construct a panel of coal-fired boilers between 1985 and 2017 using data from the EIA, specifically annual forms EIA-767, EIA-860 and their predecessors. EIA-767 contains boiler-level data from 1985 to 2005 for steam-electric plants with nameplate capacity greater than 10 MW. EIA-860 provides data for electric power plants with nameplate capacity greater than 1 MW. It contains boiler and scrubber data commencing in 2007. Thus, we rely on EIA-767 from 1985 to 2005 and EIA-860 from 2007 onward. Once combined, the panel consists of 35,297 boiler-year observations representing 1,238 unique boilers across 429 power plants. The main variables include boiler age, capacity and scrubber installation.

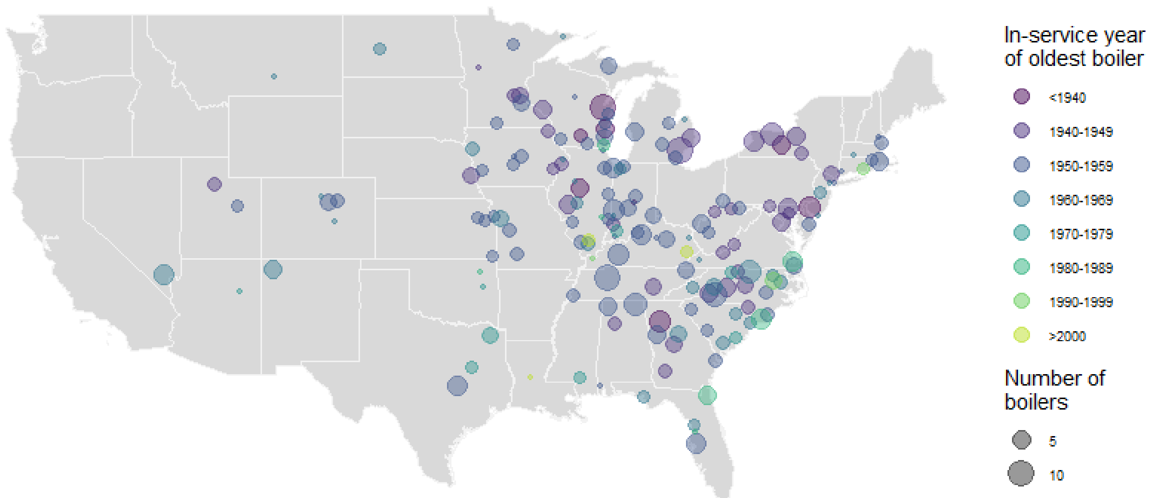
Moreover, we develop a survival indicator based on the status of the boiler reported in EIA-767. We code boilers as 'not surviving' either when their status changes to 'retired' and remains so in the following years, or when they drop from the form entirely. Retired boilers are then dropped from our sample. Between 1985 and 2017, we observe 542 boiler retirements. Figure 3.2 displays their geographic distribution. The majority of the retirements occur in the eastern half of the country, which is not unexpected given that the age and density of coal-fired boilers is higher in that region.

We also extract information from EIA-923 and its predecessor EIA-423 about the average sulfur content of purchased coal. Based on the same datasets, we construct an IV capturing the sulfur content of coal available to individual plants. To that end, we prepare a weighted average of the median sulfur content of coal from all counties using their inverse distances to the plant as weights.

[35] For example, "input coal must not contain more than 3 percent sulfur, by weight."

[36] A full appendix detailing our processes for the sulfur dioxide standards within each state is available on request.

FIGURE 3.2. Counties with boiler retirements in years 1985-2017.



Notes: Bubbles show individual counties, while their size represents the number of constituent coal-fired boiler retirements. The color indicates the in-service year of the oldest retired boiler within the county. Due to data limitations, we exclude California, Maine, Ohio and Pennsylvania.

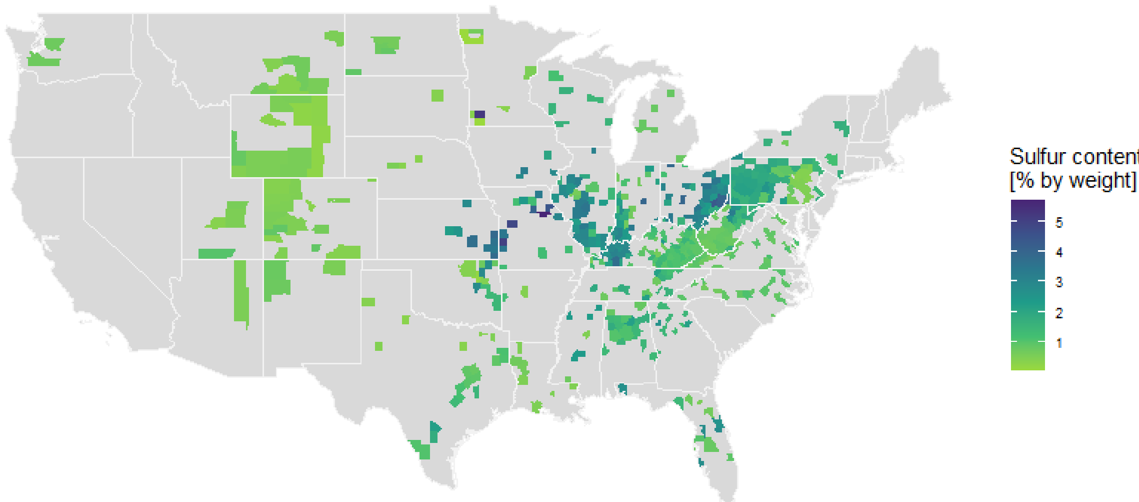
The EIA-923 and 423 provide information on power plant coal deliveries, including the source county and sulfur content by weight, while plant geographic locations are sourced from EIA-860. For any missing locations, we replace them using coordinates from the facility attributes within the EPA Air Markets Program Data. Figure 3.3a presents median sulfur content by state based on EIA-923 data, and Figure 3.3b displays the constructed sulfur IV metric for each plant in our sample.

3.4.4. Boiler operations data.

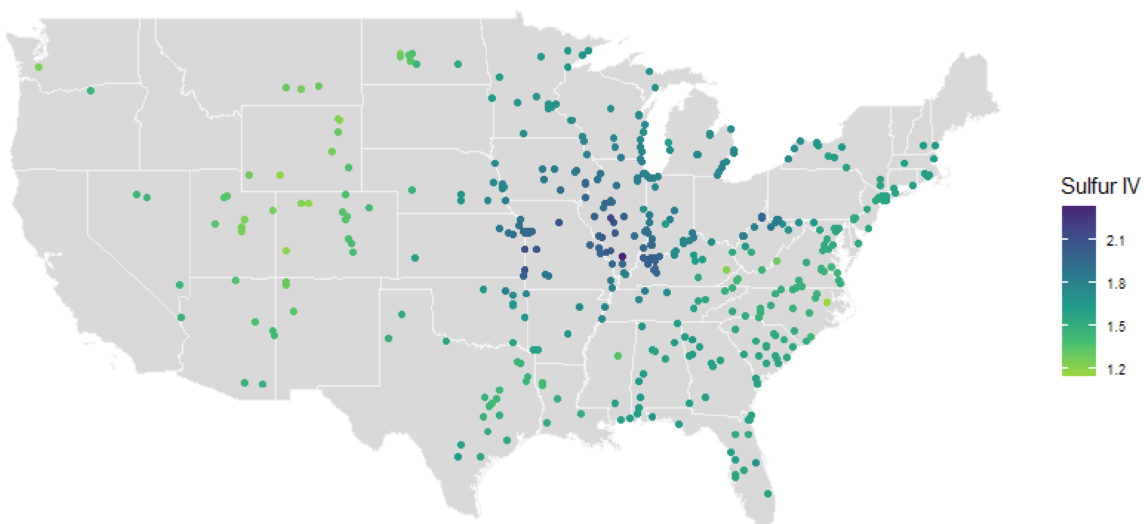
We collect boiler operations data from the Continuous Emissions Monitoring System (CEMS) published by the EPA.[37] The data are a unit-by-hour panel commencing in 1995, where coverage increases over time. It contains hours under load, generation and emissions for fossil-fired plants greater than 25 MW across the US.

[37] Part 75 of the Federal Code of Regulations (FRC), housed within the Clean Air Act Title IV, requires coal, oil and natural gas units to install and use CEMS. The EPA uses the data to ensure compliance with various stationary emissions standards and programs, including the Acid Rain Program.

Figure 3.3. Associating available coal to all coal-fired power plants



(a) Median sulfur content of coal by county.



(b) Weighted average of median sulfur content of available coal by inverse distance for all coal-fired power plants.

Unfortunately, there are a couple of challenges associated with CEMS data. First, EPA and EIA data lack a shared identifier. So in order to match across data sources, we rely on the EPA's

Power Sector Data Crosswalk, which associates EPA units with EIA boilers.However, the crosswalk does not allow for a unique match of all boilers in our data to CEMS records.[38]

Second, CEMS reports gross generation, which includes plant auxiliary loads. For our purposes, we require net generation, or equivalently, the amount of energy transmitted to the grid. To determine net generation, we scale the CEMS data by a net-to-gross generation ratio. The EIA-923 and predecessor forms, EIA-906 and EIA-920, summarize monthly data for units above 10 MW. Page 1 in the dataset provides a plant-by-fuel-by-month panel of net generation. Data for utility plants are available from 1970, while non-utility plants are available from 1999.[39] We calculate the ratio by aggregating CEMS gross generation and EIA net generation to the plant-by-month level. Then, taking the quotient of net-to-gross generation results in a plant-specific ratio which can be applied across all CEMS generation data.

3.4.5. Electricity market data.

To supplement the boiler and regulatory data mentioned above, we collect annual electricity market data, including demand, aggregate capacity and fuel prices. Annual electricity demand at the state level is sourced from the EIA State Energy Data System, while we procure utility-level demand from EIA-861. For the latter, we use the "Sales to Ultimate Customers" table which is available from 1990 onward and represents a balanced panel by utility. We use the demand data to compute year-over-year demand growth rates by state and utility.

For capacity data, we utilize the "Existing Nameplate and Net Summer Capacity by Energy Source, Producer Type and State" table based on annual data reported in form EIA-860. The data is a panel of nameplate capacity by state, fuel source and producer type from 1990 onward. We aggregate over all producer types to generate a panel of state capacity. We use the result to compute a measure of competitive pressure from other generators.

[38] The EPA Power Sector Data Crosswalk is a contemporary mapping. It lacks matches for units which have since been retired. An improved historical matching could be achieved through a comparison of the EPA facility attributes dataset and EIA-860. Additionally, some matching difficulties relate to the fact that the purpose of CEMS is to monitor emissions and determine compliance with various emissions standards. Thus, each unit is associated with a 'smokestack,' which does not always directly translate into boilers.

[39] Page 4 in the EIA-923 dataset provides a generator-by-month panel of net generation. However, this format was first released in 2008.

For input fuel prices, we again turn to EIA-923 and its predecessor EIA-423. These forms provide monthly fuel receipts and cost data for fossil-fired plants with a nameplate capacity of at least 50 MW. The data are available from 1972 onward, where the cost data includes the fuel price and haulage. Using the data, we then perform the following three aggregations: plant-year coal prices weighted by mass; state-year coals price weighted mass; and, state-year gas prices weighted by volume. We then calculate another competitive pressure metric: the ratio of procurement and delivery costs of gas to those of coal. For those plants where we have specific fuel receipts, the ratio is plant specific; otherwise, we rely on a state based measure. In states where the prices of gas or coal are not available, we use the country-level average for the given year.

3.5. Results

In this section, we present our results. We begin by comparing grandfathered and non-grandfathered boilers across a number of characteristics. This is followed by our main regression results for utilization, survival and emissions. Finally, we discuss heterogeneity in our results across years and hours.

3.5.1. Grandfathered versus non-grandfathered boilers.

First, we want to understand how boilers that initially enjoyed NSR grandfathering status differ from ones exposed to NSR regulation. As discussed in Subsection 3.3.6, systematic differences could pose a threat to causal interpretation. We find measurable differences in baseline observables between grandfathered and non-grandfathered boilers. See Table 3.B.1 in Appendix 3.B.

Non-grandfathered boilers are younger, larger, and regulated more stringently. They tend to be located closer to the Northeast and are not as frequently operated by investor-owned utilities. Naturally, both their in-service and retirement years are later. For outcome variables, our naive comparison of utilization and retirement share means produces differences counter to expectation, such that grandfathered plants are used less and are more likely to have retired. Regarding sulfur dioxide emissions, our naive comparison agrees with expectations and shows that grandfathered plants are more emissions intensive. Given that the two groups clearly differ, our empirical approach incorporates many of the variables in Table 3.B.1 as controls.

3.5.2. Examining the effects of grandfathering.

Table 3.1 presents results from the estimation of Equation (3.7), where outcome variables differ across panels and controls differ across columns. Columns (1) through (4) include boilers that are run by investor-owned utilities (IOU) as well as commercial and industrial boilers. These groups define boilers for which we can clearly identify the applicable NSR regime. Column (5) uses the whole sample. Column (6) is restricted to IOUs only. Table 3.2 provides the first-stage regression results for Columns (4) and (6).

A central result is that the direct effect of NSR grandfathering increases boiler utilization, survival and emission rates in the sample at large. For emissions, the indirect effects of grandfathering drive additional increases. These results are stable to the inclusion of additional controls. For small utility-owned, commercial, and industrial boilers exempted from NSPS and located in attainment regions without local sulfur dioxide regulations, NSR grandfathering encourages additional utilization exceeding 2,500 hours or over 100 days per year. Under similar restrictions, NSR grandfathering increases survival by around 3.5 percentage points, and is associated with direct and indirect increases in emissions of around 4.5 lbs of SO_x per MW per hour. The effects seem to be particularly strong for IOUs.

When other types of boilers, such as state, municipal boilers and units owned by independent power producers, are included, the effects are less pronounced. For utilization, for instance, they almost halve. This could be due to the objectives governing the utilization of these units or due to the difficulty of assigning them the proper grandfathering status.

Exposure to either NSPS or state regulations is associated with weaker grandfathering effects, while leaving boilers subject to NSR mostly unaffected. This is sensible as NSPS and state programs restrict boiler emissions, albeit less stringently than NSR. Similarly, boilers located in non-attainment regions exhibit reduced effects of NSR grandfathering. This could be driven by many effects. First, states could be undertaking additional regulatory or administrative steps to

TABLE 3.1. Main regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	*OLS*	*OLS*	*OLS*	*IV*	*IV*	*IV*
	IOU+	*IOU+*	*IOU+*	*IOU+*	*IOU+*	*All*	*IOU*
Panel A: Utilization							
GF	832.50***	2530.81***	2652.22***	2585.72***	2615.17***	1468.64***	2690.52***
	(13.36)	(9.70)	(9.87)	(9.11)	(9.57)	(8.89)	(7.96)
size	1288.69***	3147.40***	3211.40***	3343.48***	3062.66***	2099.43***	2979.46***
	(9.74)	(8.83)	(8.70)	(8.40)	(7.65)	(9.13)	(6.09)
GF × size		−1992.83***	−2129.91***	−2331.10***	−1992.95***	−732.68**	−1971.26***
		(−5.86)	(−6.06)	(−6.23)	(−5.31)	(−3.21)	(−4.28)
NAAQS		1077.44***	1098.48***	1189.47***	1090.48***	1017.13***	1150.47***
		(6.87)	(6.26)	(6.53)	(6.21)	(4.88)	(5.81)
GF × NAAQS		−1822.90***	−1890.20***	−1548.87***	−1912.14***	−1816.59***	−2066.24***
		(−9.42)	(−8.85)	(−7.28)	(−8.98)	(−7.88)	(−8.60)
MMBTU		28.02	28.38	27.44	33.35	130.70**	34.60
		(0.57)	(0.57)	(0.57)	(0.67)	(2.81)	(0.68)
GF × MMBTU		−412.20***	−415.90***	−308.55***	−415.19***	−507.28***	−426.74***
		(−7.16)	(−7.20)	(−6.57)	(−7.18)	(−10.48)	(−7.02)
SO2cont IV					−137.74	21.71	−280.39*
					(−1.20)	(0.24)	(−2.49)
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Utility FE	*X*	*X*	*X*	*X*	*X*	*X*	
Market Controls			*X*	*X*	*X*	*X*	*X*
Sulfur Controls				*X*	*X*	*X*	*X*
Observations	10,782	10,782	10,436	9,762	10,436	16,291	9,927
R^2	0.289	0.304	0.301	0.294	0.301	0.296	0.289
Panel B: Survival							
GF	0.86**	3.00**	3.45***	2.67**	3.37***	2.26**	4.25**
	(3.02)	(3.24)	(3.38)	(2.74)	(3.30)	(3.27)	(3.03)
size	0.63	2.76*	3.29**	2.73*	2.84*	1.56	3.88*
	(1.16)	(2.36)	(2.58)	(2.11)	(2.02)	(1.84)	(1.99)
GF × size		−2.36*	−2.47	−1.92	−2.10	−0.00	−3.19
		(−2.02)	(−1.93)	(−1.54)	(−1.52)	(−0.00)	(−1.70)
NAAQS		2.89**	3.96***	2.97**	3.98***	3.72***	4.22***
		(3.00)	(3.33)	(2.86)	(3.34)	(3.93)	(3.40)
GF × NAAQS		−4.05***	−4.87**	−5.13***	−4.97***	−5.01***	−5.23***
		(−3.52)	(−3.26)	(−3.56)	(−3.30)	(−4.18)	(−3.34)
MMBTU		0.22	0.30	−0.20	0.31	0.11	0.39
		(0.89)	(1.03)	(−1.44)	(1.07)	(0.64)	(1.30)
GF × MMBTU		−0.60**	−0.74**	−0.34*	−0.74**	−0.74**	−0.81***
		(−3.26)	(−3.26)	(−2.18)	(−3.25)	(−2.76)	(−3.29)
SO2cont IV					−0.38	−0.92	−0.33
					(−0.54)	(−1.63)	(−0.42)
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Utility FE	*X*	*X*	*X*	*X*	*X*	*X*	
Market Controls			*X*	*X*	*X*	*X*	*X*
Sulfur Controls				*X*	*X*	*X*	*X*
Observations	15,257	15,257	12,626	11,738	12,626	19,125	11,694
R^2	0.101	0.102	0.107	0.103	0.107	0.099	0.109

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	*OLS*	*OLS*	*OLS*	*IV*	*IV*	*IV*
	IOU+	*IOU+*	*IOU+*	*IOU+*	*IOU+*	*All*	*IOU*
Panel C: Emissions							
GF	0.55***	4.73***	4.73***	4.80***	4.04***	3.68***	4.26***
	(4.19)	(12.59)	(12.59)	(12.71)	(10.12)	(12.75)	(10.64)
size	−2.00***	2.60***	2.60***	2.83***	0.56	−0.42	0.71
	(−9.19)	(6.57)	(6.57)	(7.28)	(1.00)	(−1.30)	(1.22)
GF × size		−4.77***	−4.77***	−4.92***	−2.90***	−2.83***	−3.18***
		(−10.94)	(−10.94)	(−11.45)	(−5.03)	(−7.09)	(−5.47)
NAAQS		2.40***	2.40***	1.51***	2.15***	1.74***	2.19***
		(5.19)	(5.19)	(4.59)	(5.46)	(5.46)	(5.17)
GF × NAAQS		−3.19***	−3.19***	−1.56**	−2.80***	−1.34**	−2.76***
		(−5.72)	(−5.72)	(−3.27)	(−5.59)	(−3.24)	(−5.26)
MMBTU		−0.18	−0.18	−0.14	−0.07	−0.45***	−0.07
		(−1.11)	(−1.11)	(−0.83)	(−0.42)	(−5.62)	(−0.42)
GF × MMBTU		−1.00***	−1.00***	−1.01***	−0.98***	−0.87***	−0.97***
		(−5.97)	(−5.97)	(−5.96)	(−5.60)	(−10.06)	(−5.63)
SO2cont IV					−2.28***	−1.30***	−1.78***
					(−6.03)	(−4.83)	(−4.83)
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Utility FE	*X*	*X*	*X*	*X*	*X*	*X*	
Market Controls							
Sulfur Controls				*X*	*X*	*X*	*X*
Observations	10,227	10,227	10,227	9,706	10,227	16,181	10,049
R^2	0.419	0.432	0.432	0.438	0.440	0.407	0.443

Notes: Columns (1) to (4) are estimated using OLS, while Columns (5) to (7) use 2SLS and leverage sulfur content of the available coal as an instrument for sulfur content of the combusted coal. The unit of observation is boiler-year. The *IOU* specification restricts the sample to boilers belonging to IOUs, while the *IOU+* specification restricts to commercial, industrial and IOU boilers. *All* uses all available boilers. Utilization and emissions estimations are based on data between 1995 and 2018, survival estimations on 1985 to 2017. We use robust standard errors. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, t-statistics are in parentheses.

control their sulfur dioxide emissions beyond the sulfur regulations measured through our $NAAQS$ variable. These regulations likely target the most polluting boilers, such that grandfathered boilers would be most impacted. Second, in non-attainment counties there may be more public awareness of pollution problems. Press coverage of the local damages from sulfur emissions, politicians keeping a close eye on dirty facilities, and other forms of social pressure on polluters could reduce the advantage of grandfathering. On a related point, in non-attainment counties, facilities could engage in regulatory avoidance, as the likelihood of their actions and emissions attracting attention is higher (Raff and Walter, 2020). Through regulatory avoidance, boilers would voluntarily limit the advantage provided by grandfathering provisions.

The utilization and emissions effects also decrease with boiler capacity. For utilization this could be driven by the fact that larger boilers generally run most of the time; hence, the number of hours that a boiler can run additionally is limited. For emissions, the explanation for the finding is less straightforward. It could relate to the fact that scrubber installation is generally more cost-efficient for larger units. This could cause larger units to more frequently adapt pollution abatement equipment for compliance with cap-and-trade programs even if they were not subject to NSR. It could also relate to the fact that units with higher gross generation were more likely to be targeted by EPA for enforcement of the modification rule Chan and Zhou (2021), causing them to engage in regulatory aversion Keohane, Mansur and Voynov (2009).

Table 3.2. Main regression first-stage results

	IOU+	*All*	*IOU*
sulfur	2.62***	2.35***	2.83***
	(30.29)	(37.36)	(31.32)
GF	−0.39***	−0.21***	−0.42***
	(−7.47)	(−4.52)	(−7.73)
size	−1.18***	−0.70***	−1.34***
	(−16.81)	(−10.04)	(−18.67)
GF × size	1.04***	0.65***	1.09***
	(13.95)	(8.77)	(14.30)
NAAQS	−0.08	−0.07	−0.00
	(−0.71)	(−0.64)	(−0.04)
GF × NAAQS	−0.12	−0.05	−0.14
	(−1.05)	(−0.46)	(−1.16)
MMBTU	0.03***	−0.04***	0.02**
	(3.77)	(−4.01)	(2.68)
GF × MMBTU	0.04***	0.03**	0.04***
	(4.51)	(2.65)	(5.16)
Year FE	*X*	*X*	*X*
State FE	*X*	*X*	*X*
Utility FE	*X*	*X*	
Market Controls	*X*	*X*	*X*
Observations	13,365	19,750	12,503
R^2	0.596	0.481	0.590

Notes: The dependent variable is sulfur dioxide content of the combusted coal. All specifications are estimated using OLS. The unit of observation is boiler-year. The *IOU* specification uses only boilers belonging to IOUs, while the *IOU+* specification uses commercial, industrial and IOU boilers. *All* uses all available boilers. We use robust standard errors. Significance is represented as *** for $p<0.001$, ** for $p<0.01$, and * for $p<0.05$; while, *t*-statistics are in parentheses.

We can also calculate the average total effect of NSR grandfathering while accounting for: interaction effects between grandfathering and state regulations, between grandfathering and boiler size, and its indirect effects. Relying on the specification from Column (5) in Table 3.1, we calculate the effect of grandfathering for each observations in our sample. Taking averages of the calculated effects, we find that grandfathering is associated with approximately 787 additional hours of operations annually, 2.05 pounds of additional SO_2 emissions per MW of capacity per hour run, and with a 1.5 percent increase in the probability of surviving an additional year. Note that these effects are high, especially given that we are looking at the pool of all boilers that initially enjoyed grandfathering status and which many of them lost over time.[40]

The remaining covariates, including age and size effects are coherent with economic intuition. We observe substantial heterogeneity in the effects across years and states as captured by fixed effects.

Given the strong utilization advantage associated with grandfathering, we perform the net-to-gross generation analysis as presented in Equation (3.2). Table 3.3 presents the results using data restricted to 2008 to 2017 due to limited availability of generation information.[41] Column (1) lacks covariates and, thus, its intercept represents the pure weighted average generation ratio for non-grandfathered plants, 92.1 percent. In this case, the coefficient on our grandfathering indicator is negative implying that grandfathered plants are less efficient in exporting electricity to the grid. However, grandfathered boilers differ systematically from their non-grandfathered counterparts. They are inherently older and tend to be smaller on average. When controlling for these two characteristics, the sign on grandfathering reverses and is statistically significant at the 99.9 percent level as can be seen in Column (2).

This correlation implies that grandfathered boilers tend to be more efficient in delivering electricity to the grid. It also supports the assumption that they are less costly to operate. However, this effect does not seem to be the main driver of the differences in utilization given its small size: the results suggest that the net-to-gross generation ratio is 0.2 percentage points higher for grandfathered units, but the absolute level of the ration is usually above 90 percent.

[40] Among others, between years 1999 and 2015, 275 boilers became subject of investigation connected to their NSR status under the modification rule, which resulted in settlements and loss of grandfathering status (Chan and Zhou, 2021).

[41] Additional detail on the data used in Table 3.3 can be found in Subsection 3.4.4.

Table 3.3. Net-to-gross generation ratio regressions

	(1)	(2)
Grandfathering	-0.006^{***}	0.002^{***}
	(-13.40)	(3.93)
Age		X
Size		X
Observations	69,309	69,309
R^2	0.003	0.050
Adjusted R^2	0.003	0.050

Notes: This table reports results from two weighted least squares regressions based on Equation (3.2). The dependent variable is net-to-gross generation ratio, while the weights are based on monthly durations. Column (1) essentially represents the pure weighted average, while Column (2) presents one conditional on age and size. They rely on CEMS and EIA-861 data from 2008 to 2017. Significance is represented as *** for $p<0.001$, ** for $p<0.01$, and * for $p<0.05$; while, t-statistics are in parentheses.

3.5.3. Examining heterogeneous effects.

The above analyses assume constant effects of grandfathering across time. However, it is possible that over years, with a changing regulatory landscape and market conditions, the advantage of grandfathering may also change. Such heterogeneous effects are important when assessing whether the need for corrective policies remains.

For utilization effects, their distribution over the course of a day matters as well. Different types of resources tend to be marginal in different hours. So, depending on when the additional utilization happens, grandfathered boilers could push out different resource types. As a consequence, the utilization channel can have different marginal emission impacts and, thus, different welfare implications depending on the exact time distribution.

We, thus, present results from an investigation of heterogeneous grandfathering effects across both years and hours. To that end, we first modify Columns (3) and (4) from Table 3.1 by combining the grandfathering indicator and year fixed effects into a series of interaction terms. Figure 3.1 presents the results. For utilization and survival, results are similar in that they are positive, relatively stable and significant up until around 2010 when many new environmental rules were announced. For utilization prior to 2010, NSR grandfathering tends to add around 1,000 hours per year. After 2010, the effect is not statistically significant. Grandfathering increases the chance of survival assuming the boiler is present in the previous year by around 0.17 percentage points. Though they remain significant, its results are far less stable after 2010. For emissions, the effects are decreasing over time, reflecting the fact that many of the boilers that were initially grandfathered decided over time to install scrubbers, for instance to reduce their compliance costs with Acid Rain Program, or lost their grandfathering status as a result of the modification rule.

To understand the hourly effects of grandfathering, we use CEMS data and run 24 separate regressions of Equation (3.7) for each hour of the day. Figure 3.2 presents the resulting estimates for the effects of grandfathering on utilization. From the plot, the effect is stable and significant across all hours of the day. For every hour, NSR grandfathering is associated with an increase in utilization of between 0.15 and 0.17 hours, which is equivalent to around 10 minutes per hour. Evidently, grandfathered plants were operated as baseload plants.

3.5.4. Robustness checks.

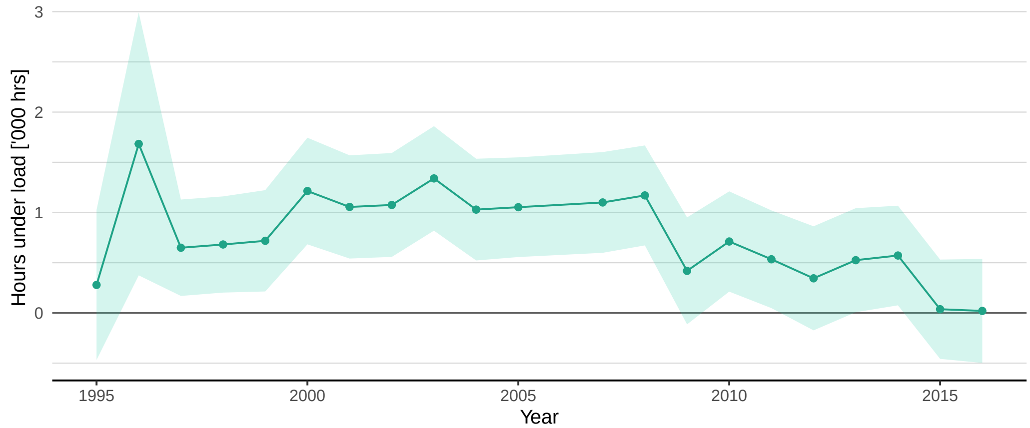
In this subsection, we check the robustness of our main results using two methods. First, we restrict the boiler vintages to those nearest to the implementation of NSR. Second, we adopt a conservative definition of NSR grandfathering based only on its implementation date and boilers' in-service years.

Restricting the boiler vintages.

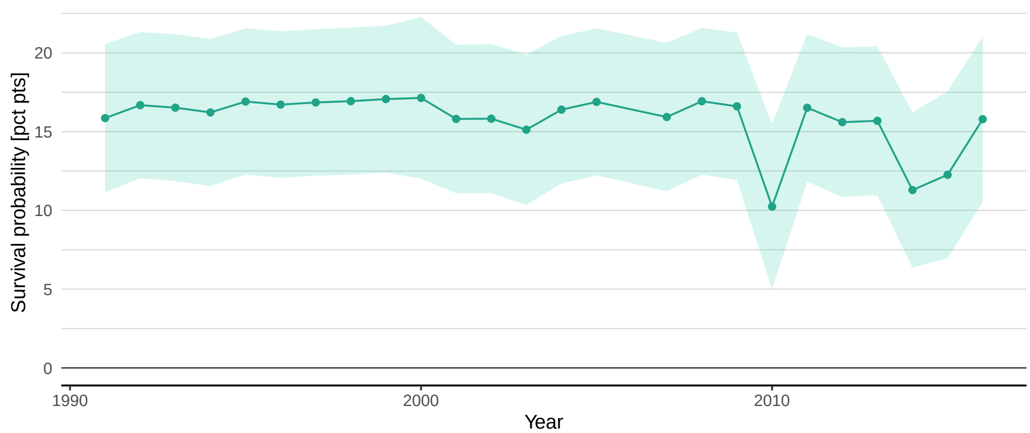
A potential problem with our approach is that, as it uses boilers built in different decades, unobserved improvements in boiler technology could be confounding the inference and biasing our results. Estimations using boilers constructed just before and just after the introduction of NSR could, thus, provide cleaner results. That is, a more narrow sample implies that the support across the two groups—grandfathered and non-grandfathered boilers—is better aligned. However, narrowing the sample increases the likelihood of incorrect assignment grandfathering status.[42] Thus, we restrict the sample to boilers with in-service years between 1970 and 1994. We anticipate that this

[42] See Section 3.4.1 for further details.

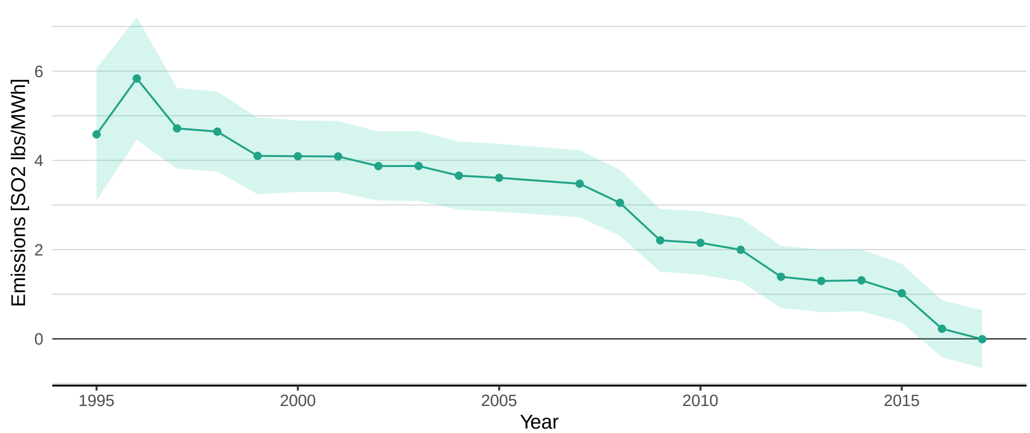
Figure 3.1. Yearly effects of NSR grandfathering.



(a) Hourly utilization. Coefficients derived from a regression using CEMS data and performed by including grandfathering-year interactions in Column (4) from Table 3.1.

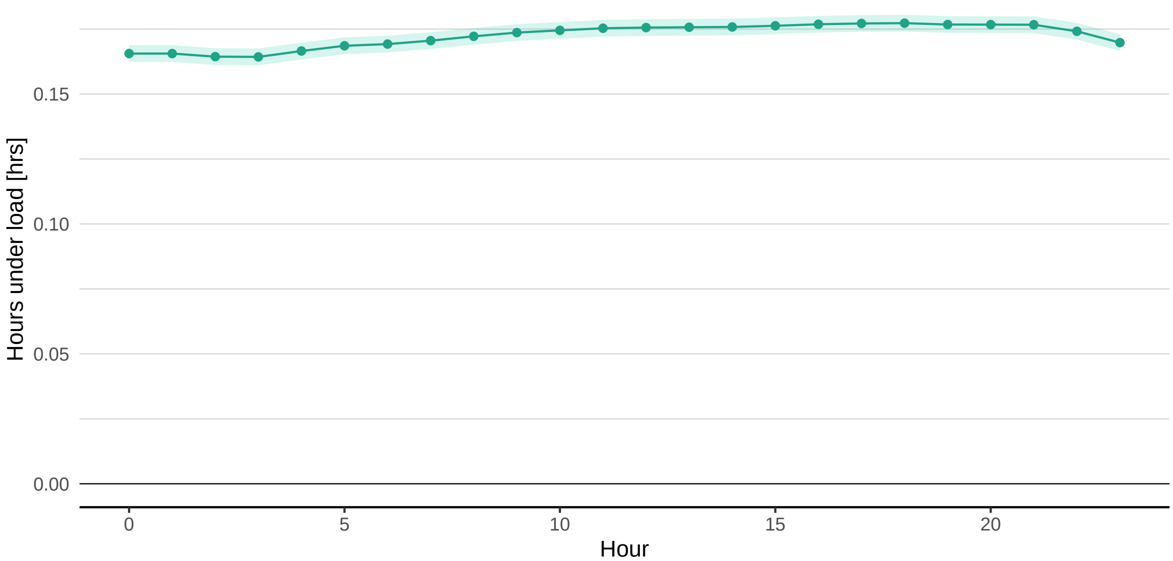


(b) Survival. Coefficients derived from a regression performed by including grandfathering-year interactions in Column (3) from Table 3.1.



(c) Sulfur emissions rate. Coefficients derived from a regression based on CEMS data and performed by including grandfathering-year interactions in Column (4) from Table 3.1.

Figure 3.2. Hourly effects of NSR grandfathering on utilization.



Notes: Coefficients derived from a set of regression equivalent to Column (4) from Table 3.1, where the sample is limited to that for the specific hour.

time range restricts variation in boiler technologies while also limiting the share of boilers with mis-assigned grandfathering status. This leaves us with 125 grandfathered and 291 non-grandfathered boilers, out of which 54 and 152 are operated by IOUs, respectively.

The resulting estimates, shown in Tables 3.D.1 and 3.D.2 in Appendix 3.D, are consistent with our main findings but of smaller magnitude. This may be due to the heightened significance of noise within our grandfathering status indicator.

Grandfathering status.

We now address the robustness of our main results by adopting a "conservative" assignment of NSR grandfathering status, i.e. by assuming that all boilers with in-service years after the passage of the relevant NSR rules were subject to these rules, notwithstanding when their construction commenced. The cut-off year for grandfathering is thus 1979 for boilers generating electricity for utility sales with capacity above 73 MW, 1987 for commercial and industrial boilers above 10 MW, and 1990 for commercial and industrial boilers with capacity between 1 and 10 MW. Such an approach guarantees that all non-grandfathered boilers are correctly classified, though it is susceptible to false negatives. That is, some boilers that actually were grandfathered are unintentionally marked as non-grandfathered.

Table 3.D.3 in the Appendix 3.D shows the results. They are again consistent with our main specification but of smaller magnitude, likely due to a higher number of boilers incorrectly classified as non-grandfathered.

3.6. Conclusion

The Clean Air Act is the centerpiece for air pollution control within the US. Nevertheless, some of its aspects remain relatively little understood. This holds true, among others, for New Source Review and its associated grandfathering provisions. Despite their importance for the operations of regulated units and for sulfur emissions, only a small set of papers addresses them empirically.

We offer new insight into the impacts that NSR grandfathering provisions had on the operation of coal boilers with respect to both their utilization and retirement decisions. We also show how NSR grandfathering allowed incumbent boilers to maintain high sulfur dioxide emissions, even decades after the implementation of NSR. We combine various sources of data on boilers, coal, electricity markets, and federal sulfur dioxide regulations between 1985 and 2018. We also create a dataset of state-level sulfur dioxide regulations. Our econometric analysis, aided by the differences of NSR's applicability across boilers of various size and type, documents how the cost wedge introduced by grandfathered boilers biased the outcomes in the sector. We find that, on average, grandfathering status was associated with 787 additional hours under load annually and a 1.5 percentage point increase in the probability of surviving an additional year. This suggests that NSR provisions pushed generation towards less efficient incumbent boilers. The effects were particularly pronounced for small boilers in attainment counties and for the early years of our sample. We also show the importance of state regulations in limiting the perverse effects of NSR grandfathering.

A motivating factor behind this work was the sustained usage of vintage regulation provisions, especially in an environmental context. For policymakers, our analysis represents a warning for the implications of passing grandfathering provisions without well-designed sunset clauses, especially when the regulated asset is long-lived.

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Appendix

3.A. Data overview

Table 3.A.1. Variables summary

Variable	Description	Source
$hours_{it}$	Dependent variable representing the number of hours boiler i operated in a year t	EPA CEMS
$survive_{it}$	Dependent binary variable equal to one if boiler i continued operation in year $t+1$	EIA-767; EIA-860
$emissions_{it}$	Dependent variable representing sulfur dioxide emissions per hour for boiler i in year t	EPA CEMS
GF_i	Indicator variable equal one if boiler i was covered by the grandfathering provision when NSR was enacted	EIA-767; Own research
$NAAQS_{jt}$	Indicator variable equal to one if county j is a non-attainment region for sulfur dioxide under NAAQS	EPA Green Book
$MMBTU_{it}$	Variable representing the more stringent of the local sulfur regulation and New Source Performance Standard, if applicable, for boiler i in year t expressed as an inverse	Own research
$price_{it}$	Effective permit price faced by boiler i in year t for a short ton of sulfur dioxide emissions	Federal Register; EPA
$SO2cont_{it}$	The average sulfur content of coal used by boiler i during year t	EIA-923 & EIA-423
$sulfur_{it}$	IV based on the average sulfur content of coal available to boiler i during year t	EIA-923 & EIA-423; EIA-860 & EPA
age_{it}	Boiler i age in years	EIA-860
$size_i$	Boiler i capacity in GW	EIA-767; EIA-860; EPA
$growth^s_{jt}$	Percentage growth in state j electricity demand in year t	EIA State Energy Data System
$growth^u_{it}$	Percentage growth in utility electricity demand faced by boiler i in year t	EIA-861
$GasCap_{jt}$	Competitive pressure from natural gas units measured as their total capacity in state j during year i	EIA-860

Variable	Description	Source(s)
$VRECap_{jt}$	Competitive pressure from variable renewable energy, including wind and solar, measured as their total capacity in state j during year i	EIA-860
$GasPress_{it}$	Competitive pressure from gas units measured as the ratio of procurement and delivery costs of gas to coal for boiler i in year t	EIA-923 & EIA-423
α_j	State fixed effects	EIA-767; EIA-860
μ_m	Owner type fixed effects, including utility, independent power producer, state, coop, etc.	EIA-860
η_t	Year fixed effects	

3.B. Grandfathered versus non-grandfathered boilers

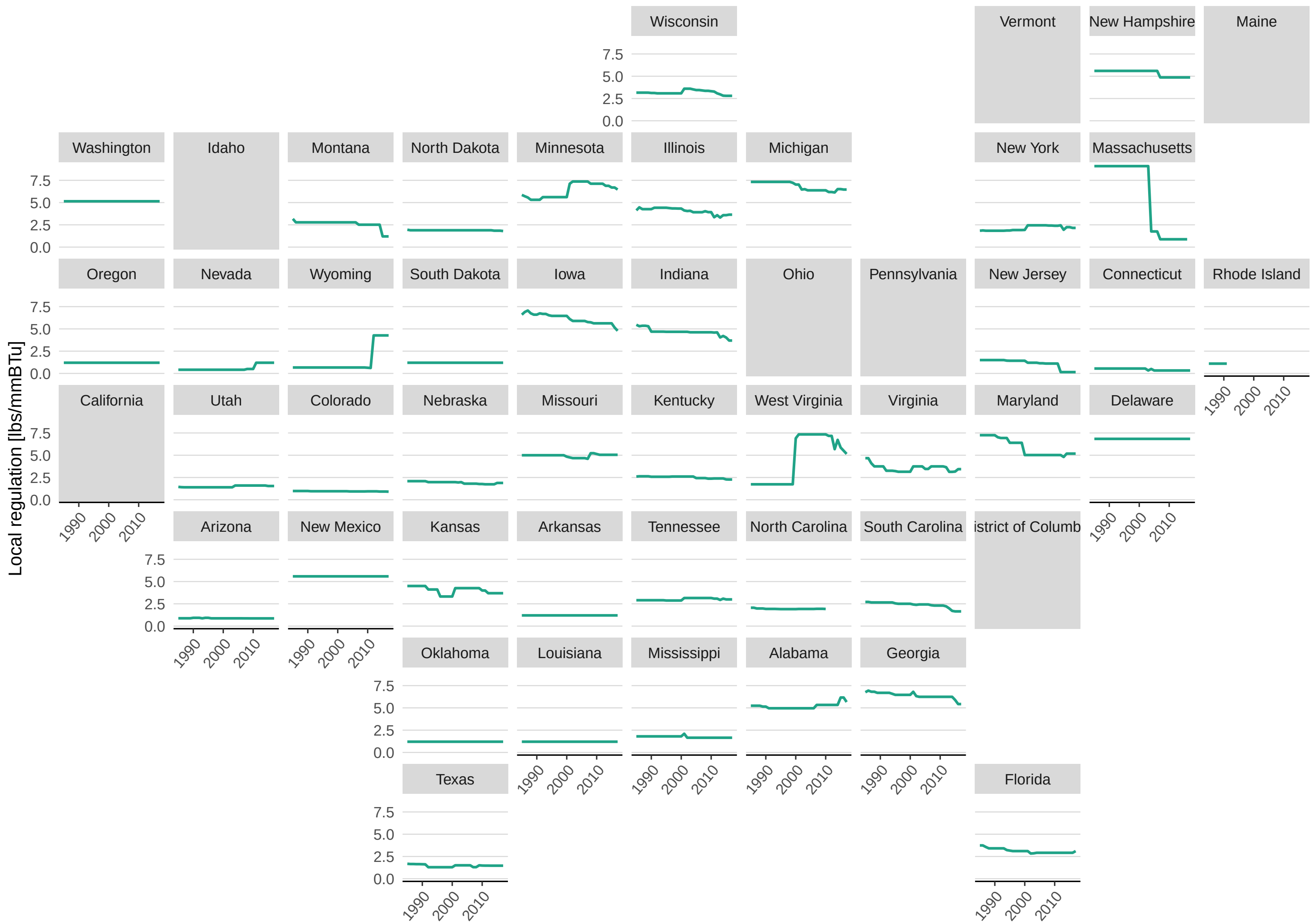
Table 3.B.1. Average characteristics of boilers by NSR grandfathering status

Variable	Grandfathered	Non-Grandfathered	Difference
Nonattainment	0.07	0.01	0.05^{***}
	(0.18)	(0.07)	[7.24]
Acid Rain Program	0.95	1.00	-0.05^{***}
	(0.22)	(0.00)	[−7.62]
Applicable Non-NSR Emission Standard [lbs/mmBTu]	5.31	4.54	0.78^{**}
	(3.07)	(3.17)	[3.14]
Latitude	38.67	37.51	1.15^{**}
	(4.02)	(4.75)	[3.16]
Longitude	−87.21	−90.90	3.69^{***}
	(8.87)	(9.82)	[4.85]
Capacity	251.31	497.17	-245.86^{***}
	(243.45)	(247.36)	[−12.62]
Age	36.78	12.05	24.73^{***}
	(11.07)	(5.99)	[44.71]
Inservice Year	1,962.66	1,993.05	-30.39^{***}
	(12.18)	(10.96)	[−34.66]
Retirement Year	2,010.99	2,013.52	-2.52^{**}
	(8.03)	(4.09)	[−2.92]
Retire	0.51	0.14	0.37^{***}
	(0.54)	(0.35)	[12.36]
Duration† [hr/yr]	6,071.61	7,104.42	$-1,032.81^{***}$
	(1,936.48)	(1,410.65)	[−8.02]
Generation† [GWh/yr]	1,602.98	3,366.25	$-1,763.27^{***}$
	(1,571.93)	(1,637.21)	[−11.52]
SO2 Emissions† [lbs/mmBTu]	1.03	0.35	0.68^{***}
	(0.76)	(0.25)	[19.87]
Weighted Average Mine Sulfur Content [% weight]	1.66	1.63	0.03
	(0.19)	(0.22)	[1.92]
Share of Co-operatives	0.06	0.10	−0.04
	(0.23)	(0.30)	[−1.79]
Share of Commercial	0.01	0.02	−0.00
	(0.11)	(0.13)	[−0.27]
Share of Federal	0.04	0.08	−0.04
	(0.20)	(0.27)	[−1.77]
Share of Investor-Owned	0.56	0.41	0.15^{***}
	(0.50)	(0.49)	[3.74]
Share of Industrial	0.01	0.03	−0.01
	(0.12)	(0.16)	[−0.99]
Share of Municipal	0.06	0.09	−0.03
	(0.24)	(0.29)	[−1.35]

Variable	**Grandfathered**	**Non-Grandfathered**	**Difference**
Share of Political	0.07	0.10	−0.03
	(0.25)	(0.30)	[−1.48]
Share of IPPs	0.12	0.13	−0.01
	(0.32)	(0.34)	[−0.54]
Share of State	0.07	0.05	0.02
	(0.26)	(0.21)	[1.39]
Number of Boilers	1,030	192	

Notes: This table displays average characteristics by NSR grandfathering status. Standard deviations are in parentheses, with t-statistics of the difference between 'grandfathered' and 'non-grandfathered' boilers in brackets where *** p¡0.001; ** p¡0.01; * p¡0.05. All variables utilize the full extent of our dataset, except for those from CEMS which are from 1997 onwards and are identified with a †. Each row is a separate calculation, and is not conditional on the other variables reported here. Co-operatives, commercial, federal, investor-owned, industrial, IPPs (independent power producers), municipal, political, and state refer to boiler ownership.

FIGURE 3.C.1. Mean state regulations by year



Notes: The line shows local emissions requirements averaged over active boilers in a given year. Absence of pollution limits for individual boilers was coded as a standard of 9 lbs/mmBTU. Grey boxes indicate states for which we either were unable to compile the information on local regulations or states that had no active coal boilers.

3.D. Robustness checks

This appendix presents results for the robustness checks discussed in Section 3.5.4.

3.D.1. Restricting the boiler vintages.

First, we perform a robustness check of our main results in Table 3.1 by restricting the sample to boilers taken into service in years 1970 to 1994. Table 3.D.1 reports the main regression results, while the first three columns in Table 3.D.2 presents the results of the corresponding first stage regressions.

Table 3.D.1. Robustness regression results: Boilers born near the passage of NSR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	*OLS*	*OLS*	*OLS*	*IV*	*IV*	*IV*
	IOU+	*IOU+*	*IOU+*	*IOU+*	*IOU+*	*All*	*IOU*
Panel A: Utilization							
GF	−27.49	1098.45***	1074.67***	1058.31***	1375.20***	530.49***	695.81**
	(−0.41)	(4.48)	(4.27)	(4.25)	(5.49)	(3.62)	(2.70)
size	896.93***	2044.37***	1965.68***	1915.58***	2803.18***	1808.92***	1785.73***
	(6.31)	(6.28)	(5.90)	(5.53)	(7.49)	(8.30)	(4.85)
GF × size		−1290.01***	−1240.45***	−1479.83***	−1856.84***	−684.25**	−857.34*
		(−3.99)	(−3.75)	(−4.46)	(−5.50)	(−3.28)	(−2.53)
NAAQS		322.42*	298.72	461.57**	283.87	691.82***	238.96
		(2.25)	(1.81)	(3.02)	(1.72)	(4.31)	(1.42)
GF × NAAQS		−312.15	−243.12	−128.19	−112.77	−636.43**	−120.03
		(−1.42)	(−0.98)	(−0.67)	(−0.45)	(−2.98)	(−0.45)
MMBTU		145.08**	140.48**	76.59	120.08*	−9.37	96.49
		(2.95)	(2.80)	(1.63)	(2.36)	(−0.25)	(1.90)
GF × MMBTU		−280.60***	−272.83***	−103.86*	−292.15***	−99.33*	−228.24**
		(−4.11)	(−3.91)	(−2.39)	(−4.18)	(−2.07)	(−3.28)
SO2cont IV					541.43***	347.30**	306.90**
					(4.24)	(3.11)	(2.65)
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Utility FE	*X*	*X*	*X*	*X*	*X*	*X*	
Market Controls			*X*	*X*	*X*	*X*	*X*
Sulfur Controls				*X*	*X*	*X*	*X*
Observations	4,308	4,308	4,122	3,964	4,122	6,849	3,880
R^2	0.283	0.295	0.282	0.291	0.286	0.348	0.243

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	*OLS*	*OLS*	*OLS*	*IV*	*IV*	*IV*
	IOU+	*IOU+*	*IOU+*	*IOU+*	*IOU+*	*All*	*IOU*
Panel C: Emissions							
GF	−0.60***	0.40	0.40	0.32	−0.38	0.03	0.19
	(−3.99)	(1.31)	(1.31)	(1.02)	(−1.04)	(0.11)	(0.59)
size	1.07***	2.10***	2.10***	1.99***	0.09	0.90*	0.91
	(4.96)	(5.78)	(5.78)	(5.26)	(0.15)	(2.16)	(1.84)
GF × size		−0.97*	−0.97*	−0.87*	0.55	−1.28**	−0.10
		(−2.39)	(−2.39)	(−2.13)	(1.05)	(−3.01)	(−0.21)
NAAQS		0.88**	0.88**	0.24	0.84**	0.56	0.90**
		(2.70)	(2.70)	(0.77)	(2.61)	(1.96)	(2.93)
GF × NAAQS		−1.25**	−1.25**	−0.53	−1.18**	−0.37	−1.22**
		(−3.09)	(−3.09)	(−1.37)	(−2.91)	(−0.74)	(−3.20)
MMBTU		−0.32**	−0.32**	−0.31**	−0.26*	−0.40***	−0.26*
		(−2.93)	(−2.93)	(−2.79)	(−2.28)	(−6.19)	(−2.39)
GF × MMBTU		−0.18	−0.18	−0.17	−0.13	−0.18*	−0.13
		(−1.58)	(−1.58)	(−1.49)	(−1.11)	(−2.40)	(−1.17)
SO2cont IV					−1.44***	−0.45	−0.81***
					(−4.86)	(−1.54)	(−3.33)
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Utility FE	*X*	*X*	*X*	*X*	*X*	*X*	
Market Controls							
Sulfur Controls				*X*	*X*	*X*	*X*
Observations	4,136	4,136	4,136	4,027	4,136	6,971	4,037
R^2	0.460	0.476	0.476	0.479	0.483	0.438	0.485

Notes: Regression results using samples restricted to boilers which started their service between 1970 and 1994. Columns (1) to (4) are estimated using OLS, while Columns (5) to (7) use 2SLS and leverage sulfur content of the available coal as an instrument for sulfur content of the combusted coal. The unit of observation is boiler-year. The *IOU* specification further restricts the sample to boilers belonging to IOUs, while the *IOU+* specification restricts to commercial, industrial and IOU boilers. *All* uses all types of available boilers. Utilization and emissions estimations are based on data between 1995 and 2018, while survival estimations are based on 1985 to 2017. Estimations of survival effects are not possible given that the sample contains too few retirements. We use robust standard errors. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, t-statistics are in parentheses.

3.D.2. Grandfathering status.

Next, we check the robustness of our main results presented in Table 3.1 by adopting a conservative definition of NSR grandfathering status. Table 3.D.3 presents the main results, while the corresponding first stage results are shown in the last three columns of Table 3.D.2.

TABLE 3.D.2. Robustness regressions first-stage results

	Restricted vintages			*Alternative GF definition*		
	IOU+	*All*	*IOU*	*IOU+*	*All*	*IOU*
sulfur	2.6***	2.09***	2.87***	2.58***	2.32***	2.8***
	(20.36)	(21.07)	(21.12)	(37.18)	(38.33)	(37.77)
GF	−0.72***	−0.45***	−0.6***	−0.5*	0.21	−0.41*
	(−10.23)	(−8.64)	(−7.81)	(−2.31)	(1.07)	(1.96)
size	−1.82***	−1.04***	−1.76***	−0.87***	−0.49***	−.97***
	(−21.24)	(−16.12)	(−19.2)	(−19.69)	(−12.46)	(−21.45)
GF × size	1.31***	0.82***	1.15***	.66***	0.39***	0.6***
	(14.79)	(11.63)	(11.96)	(16.48)	(10.7)	(16.42)
NAAQS	−0.01	0.082	−0.07	.167	−0.01	0.09
	(−0.04)	(0.82)	(0.6)	(0.18)	(−.011)	(0.95)
GF × NAAQS	−0.22	−0.38***	−0.16	−.22*	−.12	−0.245*
	(−1.71)	(−3.43)	(−1.22)	(−2.33)	(−1.27)	(2.44)
MMBTU	0.02	−0.025	0.02	0.88***	−0.00	0.08***
	(0.97)	(−1.41)	(1.06)	(4.34)	(−.08)	(3.82)
GF × MMBTU	0.07***	0.08***	0.06**	−0.04*	−.018	−.03
	(2.7)	(4.37)	(2.47)	(−2.02)	(−1.29)	(−1.61)
Year FE	*X*	*X*	*X*	*X*	*X*	*X*
State FE	*X*	*X*	*X*	*X*	*X*	*X*
Utility FE	*X*	*X*		*X*	*X*	
Market Controls	*X*	*X*	*X*	*X*	*X*	*X*
Observations	5,111	8,076	4,766	13,365	19,750	12,503
R^2	0.694	0.622	0.689	0.594	0.48	0.588

Notes: The dependent variable is sulfur dioxide content of the combusted coal. All specifications are estimated using OLS. The unit of observation is boiler-year. The sample for the *Restrict vintages* columns is restricted to boilers which started their service between 1970 and 1994. The *Alternative GF definition* columns rely on a "conservative" measure of grandfathering status. The *IOU* specifications use only boilers belonging to IOUs, while the *IOU+* specifications use commercial, industrial and IOU boilers. *All* uses all available boilers. Estimations are based on data between 1995 and 2018. We use robust standard errors. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, *t*-statistics are in parentheses.

Table 3.D.3. Robustness regression results: Conservative grandfathering status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	*OLS*	*OLS*	*OLS*	*IV*	*IV*	*IV*
	IOU+	*IOU+*	*IOU+*	*IOU+*	*IOU+*	*All*	*IOU*
Panel A: Utilization							
GF^c	681.81***	583.31***	604.07***	573.49***	601.71***	219.47***	568.65***
	(12.45)	(9.02)	(9.22)	(8.99)	(9.11)	(4.29)	(8.55)
size	1391.77***	1275.82***	1225.03***	1395.14***	1188.23***	871.17***	875.79**
	(10.45)	(6.17)	(5.76)	(6.47)	(4.77)	(6.17)	(3.28)
$GF^c \times$ size		267.99	265.58	25.08	297.07	752.60***	519.78**
		(1.90)	(1.85)	(0.18)	(1.74)	(6.84)	(2.99)
NAAQS		702.08***	699.98***	755.28***	700.91***	616.47***	887.24***
		(5.10)	(4.62)	(4.94)	(4.64)	(4.28)	(5.40)
$GF^c \times$ NAAQS		−1466.13***	−1508.91***	−1123.92***	−1520.77***	−1440.73***	−1819.11***
		(−8.18)	(−7.74)	(−5.94)	(−7.79)	(−8.11)	(−8.49)
MMBTU		−349.03***	−357.23***	−332.96***	−354.65***	−63.15	−317.56***
		(−4.15)	(−4.17)	(−4.23)	(−4.10)	(−1.43)	(−3.86)
$GF^c \times$ MMBTU		49.71	57.90	141.43	55.96	−252.70***	16.53
		(0.59)	(0.68)	(1.94)	(0.65)	(−5.85)	(0.20)
SO2cont IV					−34.28	72.77	−220.85
					(−0.29)	(0.79)	(−1.92)
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Utility FE	*X*	*X*	*X*	*X*	*X*	*X*	
Market Controls			*X*	*X*	*X*	*X*	*X*
Sulfur Controls				*X*	*X*	*X*	*X*
Observations	10,782	10,782	10,436	9,762	10,436	16,291	9,927
R^2	0.287	0.298	0.294	0.286	0.294	0.293	0.282
Panel B: Survival							
GF^c	0.94***	1.07***	1.21***	0.97**	1.21**	0.70*	1.33***
	(3.47)	(3.37)	(3.29)	(2.67)	(3.29)	(2.40)	(3.52)
size	0.73	0.75	1.08	1.02	0.81	0.05	0.98
	(1.33)	(1.06)	(1.33)	(1.27)	(0.83)	(0.08)	(0.83)
$GF^c \times$ size		0.14	0.34	0.24	0.54	1.97***	0.39
		(0.29)	(0.59)	(0.43)	(0.73)	(3.36)	(0.48)
NAAQS		1.17	1.76	0.47	1.79	1.08	1.84
		(0.65)	(0.74)	(0.18)	(0.76)	(0.84)	(0.77)
$GF^c \times$ NAAQS		−2.29	−2.58	−2.51	−2.69	−2.29	−2.75
		(−1.20)	(−1.02)	(−0.92)	(−1.05)	(−1.54)	(−1.07)
MMBTU		−0.09	−0.10	−0.49**	−0.08	−0.13	−0.05
		(−0.31)	(−0.30)	(−2.99)	(−0.25)	(−0.75)	(−0.15)
$GF^c \times$ MMBTU		−0.19	−0.23	0.04	−0.24	−0.40	−0.23
		(−1.08)	(−1.03)	(0.23)	(−1.07)	(−1.80)	(−1.01)
SO2cont IV					−0.23	−0.85	−0.17
					(−0.33)	(−1.50)	(−0.22)
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Utility FE	*X*	*X*	*X*	*X*	*X*	*X*	
Market Controls			*X*	*X*	*X*	*X*	*X*
Sulfur Controls				*X*	*X*	*X*	*X*
Observations	15,257	15,257	12,626	11,738	12,626	19,125	11,694
R^2	0.101	0.102	0.106	0.102	0.107	0.099	0.108

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	*OLS*	*OLS*	*OLS*	*IV*	*IV*	*IV*
	IOU+	*IOU+*	*IOU+*	*IOU+*	*IOU+*	*All*	*IOU*
Panel C: Emissions							
GF^c	0.78***	1.04***	1.04***	1.02***	0.95***	1.44***	1.02***
	(6.11)	(7.39)	(7.39)	(7.09)	(6.75)	(11.71)	(7.36)
size	−1.95***	−1.12***	−1.12***	−0.94**	−2.49***	−2.98***	−2.45***
	(−8.95)	(−4.06)	(−4.06)	(−3.29)	(−6.31)	(−12.16)	(−6.06)
$GF^c \times$ size		−0.38	−0.38	−0.45*	0.71*	0.23	0.60
		(−1.80)	(−1.80)	(−2.11)	(2.21)	(1.08)	(1.90)
NAAQS		1.59***	1.59***	0.77**	1.81***	0.54	1.74***
		(3.74)	(3.74)	(2.90)	(4.81)	(1.67)	(4.31)
$GF^c \times$ NAAQS		−2.39***	−2.39***	−0.82	−2.48***	−0.05	−2.33***
		(−4.52)	(−4.52)	(−1.87)	(−5.04)	(−0.12)	(−4.57)
MMBTU		−0.80***	−0.80***	−0.77***	−0.61***	−0.81***	−0.65***
		(−7.27)	(−7.27)	(−6.91)	(−5.24)	(−10.58)	(−5.67)
$GF^c \times$ MMBTU		−0.22*	−0.22*	−0.21*	−0.29**	−0.34***	−0.25*
		(−2.10)	(−2.10)	(−2.05)	(−2.75)	(−4.73)	(−2.37)
SO2cont IV					−2.18***	−1.19***	−1.67***
					(−5.66)	(−4.33)	(−4.47)
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Utility FE	*X*	*X*	*X*	*X*	*X*	*X*	
Market Controls							
Sulfur Controls				*X*	*X*	*X*	*X*
Observations	10,227	10,227	10,227	9,706	10,227	16,181	10,049
R^2	0.419	0.429	0.429	0.435	0.438	0.406	0.440

Notes: Regression results using a "conservative" definition of grandfathering, GF^c. Columns (1) to (4) are estimated using OLS, while Columns (5) to (7) use 2SLS and leverage sulfur content of the available coal as an instrument for sulfur content of the combusted coal. The unit of observation is boiler-year. The *IOU* specification restricts the sample to boilers belonging to IOUs, while the *IOU+* specification restricts to commercial, industrial and IOU boilers. *All* uses all available boilers. Utilization and emissions estimations are based on data between 1995 and 2018, survival estimations on 1985 to 2017. We use robust standard errors. Significance is represented as *** for p<0.001, ** for p<0.01, and * for p<0.05; while, *t*-statistics are in parentheses.