Three Essays on the Electricity Market, Distributed Generation, and Retail Tariff Designs

by

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Abstract

The integration of distributed energy resources (DERs) such as solar panels and batteries is crucial for the modernization and sustainability of the electricity grid. These technologies can significantly enhance grid resilience and flexibility by diversifying energy sources and reducing reliance on fossil fuels. The rapid expansion of solar and battery technologies in the past decade, driven by falling costs and supportive policies, underscores their potential to transform the electricity system. Understanding how to integrate these DERs into the electricity grid is of great importance. This thesis aims to explore the barriers to solar and battery integration and investigate how economic mechanisms, such as retail rate designs, can address these challenges and facilitate a smoother transition to a more sustainable energy system.

The first chapter of this thesis investigates whether we can use real-time pricing (RTP) and carbon taxes to reduce carbon emissions associated with battery systems. Behind-the-meter (BTM) or customer-sited battery systems can perform energy arbitrage based on the retail rate they face. Under typical time-of-use pricing, batteries will generally increase emissions because the price signal it faces does not strongly correlate with the emissions signal in the jurisdictions we consider. By incorporating RTP and carbon taxes into the retail tariff structure, we show that batteries can effectively reduce carbon emissions, as the emissions avoided through battery discharge can exceed the emissions incurred from charging and energy losses. However, RTP and carbon taxes will also decrease the private financial value

of a solar plus storage system, leading to lower investment levels.

The second chapter of this thesis looks at how transmission congestion will affect locational marginal emissions factors (MEFs) and locational environmental values of solar and batteries. MEFs measure the increase in carbon emissions if the electricity demand increases by 1 MWh. We use a regime-switching model to estimate the MEFs with or without congestion and use the congestion-weighted MEFs to calculate the environmental value of solar and batteries. We find that the emissions reductions from a rooftop solar panel located in a renewable-rich region will be reduced substantially when congestion occurs frequently. In contrast, a battery can utilize variations in MEFs with and without congestion, leading to higher emissions reduction potentials.

The third chapter of this thesis investigates whether retail electricity customers will adjust their maximum demand (i.e., highest instantaneous electricity usage) in response to changes in the level of maximum demand charges (MDCs), which charge customers based on their maximum demand rather than kWh usage. MDCs for have been proposed by a number of utilities as a way to recover fixed costs when more customers are self-generating electricity using rooftop solar rather than purchasing power from the utilities. The proponents of MDCs claim that MDCs can motivate customers to reduce peak demand and, therefore, reduce utility expenditures on grid upgrades. Our study finds that a change in the level of MDCs can have a statistically significant and modest effect on the peak demand for medium-large consumers (e.g., a medium-sized grocery store).

There are several policy implications of this thesis. First, new retail tariff designs are essential to integrate rooftop solar and batteries into the electricity market. For example, RTP and carbon taxes can be used to reduce storage-induced carbon emissions and alleviate distortions that exist in prevailing rate structures. Second, the environmental values of solar and batteries have substantial locational variations. Therefore, policies that facilitate these technologies should take into account the locational environmental value. Third, MDCs can be used to reduce the maximum demand for the electrical system, but more evidence is needed to understand their overall effectiveness, especially for large customers.

Preface

This dissertation consists of three empirical articles. I was responsible for the empirical analysis, research methodology development, and manuscript writing. My supervisors were involved in motivation, research methodology development, and manuscript editing.

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Chapter 1

The Emissions Impacts of Behind-the-Meter Battery Storage: The Role of Real-Time Pricing

1.1 Introduction

Climate change poses a fundamental and urgent threat to human society (IPCC 2022). Due to more strict environmental regulations and falling costs, renewable energy resources such as wind and solar photovoltaic (PV) have expanded rapidly worldwide (REN21 2024).[1] However, wind and solar PV only generate electricity when the sun shines or the wind blows. This intermittent nature of wind and solar presents a significant challenge to their penetration into the energy sector (Rugolo and Aziz 2012). To accommodate wind and solar, balancing sources, such as battery storage systems, will be needed to balance the fluctuations in electricity supply and demand caused by renewable intermittency.

To promote the adoption of battery storage technologies, a number of policies have been implemented to subsidize customer-sited battery storage technologies (also known as behind-the-meter or BTM battery systems), including California's Self-Generation Incentive Pro-

1. In 2023, wind and solar PV capacities increased by 119 GW and 354 GW worldwide, representing more than 90% of all renewable power additions (REN21 2024).

gram (SGIP) and New York's Reforming the Energy Vision (REV) program (Astoria 2017; CPUC 2023). However, it has been argued that these policies fail to achieve one of the fundamental goals: cutting GHG emissions (CPUC 2017; 2018a). In particular, the deployment of both utility-scale and BTM battery storage systems increases emissions almost everywhere in the US (Hittinger and Azevedo 2015; Fisher and Apt 2017).

Storage-related emissions are determined by three factors: created emissions from charging, avoided emissions from discharging, and energy loss from discharging and discharging (Arciniegas and Hittinger 2018). The first two factors are related to the electricity price signals because batteries are often used to perform energy arbitrage: charge when the energy price is low and discharge when the energy price is high. The energy loss is determined by the technical features of the battery as well as the frequency of charge and discharge. For BTM batteries, the increase in carbon emissions is mainly driven by energy loss (Fisher and Apt 2017). However, with updated battery technology that minimizes energy loss, energy arbitrage can also be an important factor that increases storage-induced emissions.[2] In particular, energy arbitrage can result in a substantial emission increase in regions that are heavily relying on coal-fired generators (Holland and Mansur 2008). In this case, batteries are often charged at night with cheap but polluting coal-fired energy and discharged when cleaner natural gas energy is used to meet peak demand.

To address storage-induced carbon emissions, the California Public Utilities Commission (CPUC) issued a mandate to reduce storage-induced carbon emissions.[3] In response, the

2. For example, one of the most popular BTM batteries, Tesla's PowerWall, has a round-trip efficiency of 90% as of 2023, meaning you can use 90% of the energy you put into the battery as energy output (Smartly Energy 2023). In contrast, some higher-end BTM batteries can achieve a round-trip efficiency of 96% at higher costs (Smartly Energy 2023).

3. In 2018, the CPUC revised its incentive policy for new storage projects under its SGIP (CPUC 2018b). The new policy requires battery owners to reduce carbon emissions by at least 5 kg per kWh of battery in order to recoup the full payment of the SGIP (CPUC 2018b). Under the new policy, each storage project will be reviewed semi-annually to ensure that the project meets the emissions requirements. Without the mandate, a battery system will emit 50 kg per kWh of battery on average (CPUC 2018b). For a medium-sized battery with 100 kWh, carbon emissions, on average, will be reduced by 5.5 metric tons. In comparison, annual carbon emissions for a typical passenger vehicle are 4.6 metric tons (EPA 2023b).

California Solar and Storage Association (CALSSA) has advocated the use of a market-based mechanism to reduce storage-induced emissions (PV Magazine, 2020). In particular, CALSSA claimed that storage-induced emissions could be reduced substantially by transitioning from the current time-of-use[4] (TOU) pricing to real-time pricing (RTP). RTP refers to a retail structure that allows the retail electricity price to change very frequently (e.g., hourly) according to the supply/demand balance of the current electricity market (Borenstein 2005). According to CALSSA, the transition from the current TOU design, which charges different prices for peak and low-peak periods, to an RTP based on the wholesale electricity price that varies more frequently, can induce BTM batteries to charge more often from green energy. The stored green energy can then be used to displace fossil fuel generation and reduce carbon emissions. Further, an RTP can increase bill savings and motivate battery investment by providing more arbitrage opportunities than the TOU rate.

Economists have long advocated RTP as it can help avoid deadweight loss associated with electricity consumption and reduce market power (Holland and Mansur 2008). However, whether it can bring additional environmental benefits for batteries is still an open question. Our paper aims to answer how RTP will affect the overall environmental outcome of battery systems coupled with solar. In particular, our paper focuses on two RTP designs: a RTP based on the wholesale electricity price and a RTP based on both the wholesale electricity price and a carbon price. The RTP plus carbon price case is interesting because it can achieve the socially optimal operation of batteries by ensuring that the time-varying social marginal cost of electricity production is reflected in the electricity rates.[5]

Under the prevalent compensation policy, the compensation rate for solar generation is closely tied to the prevailing retail prices. Because current retail prices are usually well above

4. Under a TOU rate, customers will pay varying rates throughout the day, within pre-set time periods, based on the cost of providing electricity (Faruqui and George 2005).

5. Section 1.2 provides a detailed discussion on how RTP and carbon pricing can enhance the overall efficiency of electricity markets.

the wholesale rates that RTP is based upon, implementing RTP could significantly reduce the private financial values of solar panels.[6] Thus, a move to RTP can reduce investment in solar plus storage systems that have the potential to reduce carbon emissions. Overall, RTP and carbon taxes can have ambiguous effects on the environmental outcomes of a solar plus battery system. A formal analysis is needed to quantify these effects.

In this paper, we simulate the impact of RTP and carbon pricing on carbon emissions resulting from battery systems. We compare the environmental outcomes between the RTP plus carbon pricing tariff design and several alternative retail tariff designs, including two representative TOU rates and a standard RTP without a carbon tax. Using an optimization algorithm called the DER-CAM (Distributed Energy Resources Consumer Adoption Model), we simulate the optimal operation and investment decisions for solar plus storage systems under RTP and alternative retail rate designs. In particular, we look at two cases: a case with exogenous solar and battery capacities and a case where we endogenously solve for the optimal capacities of solar and batteries. The exogenous case allows us to focus on emissions resulting from the charge and discharge decisions of batteries. The endogenous case investigates the environmental effects of solar plus storage systems in the long run, allowing for flexibility in both the operation and investment decisions.

To understand how battery operation will affect emissions, we use generation and emissions data to measure marginal emissions factors (MEFs) at different hours of the day and months of the year. The MEF captures the change in emissions for a 1 MWh change in demand. The MEFs can be used to calculate the changes in emissions resulting from changes in electricity demand caused by battery charging and discharging.

We examine the effects of RTP on two different regions to understand how the results vary with different generation mixes. Specifically, we focus on two independent system operators:

6. Some jurisdictions proposes to use a RTP plus a markup

The Electric Reliability Council of Texas (ERCOT) and The California Independent System Operator (CAISO). These two regions are interesting because they have a high penetration of renewable energy resources but different renewable portfolios. In particular, ERCOT has considerable wind capacity, while CAISO is abundant in solar energy resources and has a growing portfolio of wind generators.[7] Natural gas-fired plants generally meet marginal electricity demand in both jurisdictions, with the natural gas fleet being relatively more efficient and clean in CAISO (Potomac Economics 2023b; CAISO 2023a). While coal-fired generators play a limited role in CAISO, they are still relied upon in ERCOT for generation at night to meet marginal demand (Potomac Economics 2023b).

Our paper focuses on large commercial customers, who are the primary adopters of the BTM battery system in terms of system capacity (CPUC 2018a).[8] In addition, commercial customers, along with industrial customers, are usually the primary targets for the RTP (Borenstein 2005).[9] Throughout the analysis, our paper uses the demand profile of supermarkets as an example, but our findings are robust to other types of commercial customers.

In the short run, we find that RTP, absent carbon pricing, could lead to lower carbon emissions compared to the TOU rates, but the reductions are not substantial. While RTP can reduce carbon emissions through energy arbitrage, it also increases the use of batteries, leading to higher energy losses during charge and discharge.[10] In line with previous studies e.g., Hittinger and Azevedo 2015; Fisher and Apt 2017, we find that adding batteries to a solar system often increases carbon emissions under both RTP and TOU rates. Energy losses

7. Solar capacity in ERCOT is rapidly expanding. In 2021, solar capacity account for 40% of all capacity additions in ERCOT (ERCOT 2022). However, solar production in ERCOT remains relatively limited during our sample period.

8. Non-residential customers account for 14% of battery storage projects but 81% of battery storage capacity in California (CPUC 2018a). In particular, the CPUC highlights four types of commercial customers as the leading adopters of battery storage systems: supermarkets, hotels, offices, and schools (CPUC 2018a).

9. RTP usually targets large commercial and industrial customers because the benefits from load shifting can usually outweigh the technology costs of meter upgrades (Borenstein 2005).

10. The battery energy losses can be measured by the round-trip efficiency (RTE) of the battery, which is the percentage of electricity charged into the battery that can be retrieved for discharge (Fisher and Apt 2017).

are the primary source of storage-induced emissions in both cases. Therefore, the round-trip efficiency of the battery, which determines the magnitude of energy loss, plays a crucial role in storage-induced emissions.

Combining TOU with carbon taxes will not affect storage-induced carbon emissions, as it does not influence battery charge and discharge decisions.[11] However, we show that combining RTP with a sufficiently stringent carbon price can lead to emissions reduction from solar plus battery systems compared to a solar-only system because the emissions reductions from energy arbitrage outweigh the energy losses from battery operations. Emission reductions are more substantial in Texas, as its energy mix (with wind and coal) provides a higher MEF difference between charge and discharge. Through arbitrage, dirtier coal-fired generation is displaced by cleaner wind generation, leading to substantial emissions reduction. In addition, there are substantial seasonal effects on how RTP plus carbon taxes will affect storage-induced carbon emissions. In particular, RTP plus carbon taxes induce considerably more emissions reductions during early spring in CAISO and summer in ERCOT with high solar and wind generation.

In the long run, we find that RTP is generally insufficient to promote the adoption of solar plus storage technologies. The average rate of RTP is considerably lower than alternative rates (e.g., TOU rates). Therefore, purchasing electricity directly from the utility becomes more cost effective than self-generating electricity. As solar is compensated at the retail rate, the private financial value of solar reduces, and consumers are less motivated to install solar PV systems. As a result, under the current compensation policy, TOU rates often

11. Under RTP, carbon taxes can be passed on to customers based on the real-time emissions signals. However, constrained by the retail tariff structure, we assume that carbon taxes will be passed on to customers according to peak and off-peak periods under the TOU. As such, customers will pay an additional charge ($ per kWh) for carbon taxes that vary by periods, reflecting the average MEFs specific to that period. Consequently, carbon taxes will not alter the TOU structure, but will change the peak/off-peak rates and the rate differences across periods. Since batteries will always charge during off-peak periods and discharge during peak periods, carbon taxes will not impact storage charge and discharge decisions under TOU. See the subsection on "Carbon Taxes" in Section 1.5.5 for a detailed discussion.

outperform RTP regarding emissions reductions when investment decisions are considered. However, this is because TOU rates are over-compensating solar customers and will lead to inefficiently high solar investments.[12] We find that consumers facing RTP are willing to install solar PV systems when the costs of solar are reduced by at least 20%. In addition, the costs of batteries need to be reduced by 50% to 60% until energy arbitrage becomes profitable under the RTP plus carbon tax case.[13] Solar and battery adoption under RTP could be achieved through substantial government subsidies, reductions in solar and battery costs, or an increase in the social cost of carbon.

Our study extends the existing literature in three ways. First, our study evaluates the role of a socially optimal retail tariff design (RTP plus carbon tax) in the operation and investment of batteries from an environmental perspective. Our paper is the first to analyze such tariff design with BTM battery storage, whereas previous studies mainly focus on existing retail tariffs, such as demand charges[14] and TOU pricing.[15] For example, Fisher and Apt (2017) simulates the environmental outcomes of batteries under TOU rates in different regions, highlighting the fact that BTM batteries may increase emissions under existing tariffs in most jurisdictions. In comparison, we focus on RTP and carbon tax combinations because they represent the most efficient retail tariff designs and serve as the first-best solution to address environmental externalities. Specifically, we aim to assess the environmental effects of this socially optimal retail tariff design within a framework

12. Felder and Athawale (2014) discusses why compensating solar at retail price is over-generous for solar customers. Brown and Sappington (2017b) shows that compensating solar at the prevailing retail electricity rate will reduce aggregate welfare. Borenstein (2017) shows that the solar compensation rate is much higher than the avoided costs, and compensating solar based on avoided costs will significantly reduce the private financial value of solar.

13. A number of studies also show that the compensation for storage is not sufficient to justify the cost. For example, Muehlenbachs and Brown (2023) show that a very high benefit of avoiding outages is needed to justify the current expense of batteries.

14. Demand charges are charged based on the maximum amount of power consumed during a short time interval during a billing period (Berg and Savvides 1983).

15. Hittinger and Azevedo (2015) examines utility-scale batteries that can perform energy arbitrage based on wholesale electricity rates, which is similar to the RTP in our study. The key difference between our study and that of Hittinger and Azevedo (2015) is that we focus on BTM batteries and compare RTP with other retail tariff designs.

characterized by the rapid expansion of renewable energy. Our results shed light on the ongoing policy discussions regarding retail tariff reforms and how to use market mechanisms to reduce carbon emissions.[16]

Second, our study looks at regions with high renewable penetration, and we estimate the associated MEFs considering renewables. Previous studies (e.g., Hittinger and Azevedo 2015; Fisher and Apt 2017) examining the environmental outcomes of batteries generally assume that renewable energy resources will not be used to meet marginal demand, and thus do not affect MEFs. Consequently, batteries charging and discharging will always occur when non-renewable energy resources are on the margin. While this assumption holds true in regions with low penetration of renewable energy, it overlooks the impact of renewable energy resources in regions with high renewable penetration, potentially leading to incorrect MEF measurements. By examining the role of renewable energy sources, our study provides insight into how penetration levels of renewable energy sources will affect storage-induced carbon emissions based on MEFs.

Third, our paper differs from previous studies in considering both the operation and investment decisions of a solar plus storage system. In particular, our paper highlights the interactions between the economic values of solar and battery by looking at their investment decisions simultaneously. In contrast, most studies (e.g., Hittinger and Azevedo 2015; Fisher and Apt 2017) that look at storage-induced carbon emissions focus on battery operations in the short run, holding solar and battery capacities constant.

This paper is organized as follows. Section 1.2 provides a discussion on RTP and carbon pricing. Section 1.3 describes the economic mechanism of our analysis. Section 1.4 provides details of the data used in our study. Section 1.5 describes the methodology. Section 1.6 presents the primary results. Section 1.7 presents the results of two robustness checks.

16. See section 1.2 for more details.

Section 1.8 concludes.

1.2 Real-Time Pricing and Carbon Pricing

Economists have long advocated using market-based mechanisms such as retail rate design and carbon pricing to address carbon emissions and enhance the overall efficiency of the electricity market (Bilich et al. 2019). In particular, it has been argued that retail electricity prices should reflect the time-varying costs of electricity, and real-time pricing (RTP) is the most efficient tariff structure to achieve this objective (Borenstein 2005). In the absence of RTP, consumers will consume more electricity during peak periods and less electricity during off-peak periods relative to the optimal quantity. In addition, absent RTP, more capacity is needed to meet higher peak demand than the first-best amount of capacity in the long run (Borenstein 2005). In addition, by increasing the flexibility of electricity demand, RTP can reduce market power (Holland and Mansur 2008).

A move to RTP can bring additional environmental benefits if the RTP provides incentives for batteries to shift energy from low-cost, low-emission hours to high-cost, high-emission hours through energy arbitrage. This could occur in regions with high renewable penetration because renewable energy sources such as solar have zero marginal costs and zero emissions (Antweiler and Muesgens 2021). For example, batteries can store cheap energy from solar when there is an excessive supply of solar energy and then discharge to replace dirtier and more expensive energy resources when the solar is offline.

However, more broadly, without carbon pricing, it is likely that a move to RTP will increase emissions in regions with lower renewable penetration and higher coal generation.[17]

17. See Hittinger and Azevedo (2015) for a similar case with utility-scale batteries. In general, RTP in these regions will cause batteries to charge when coal-fired generation is on the margin because of lower electricity rates at night. Furthermore, RTP will often increase the frequency of charging, leading to higher energy losses.

Absent carbon pricing, customers face a set of distorted electricity prices that can lead to over-consumption of electricity generated from emitting sources. Although carbon pricing has been widely implemented among energy producers, carbon taxes are often passed through to consumers based on total electricity consumption instead of total emissions, leading to inefficient responses toward emissions (Fabra and Reguant 2014). It is important to include a mechanism that prices the social costs of carbon (such as a carbon tax) into the time-varying retail electricity prices (Weisbach and Metcalf 2009). Taken together, this emphasizes the value of both RTP and carbon pricing to ensure that the time-varying social marginal cost of electricity production is reflected in the electricity rates.

1.3 Economic Mechanism

This section describes how batteries can impact carbon emissions through energy arbitrage. Batteries can also impact emissions due to energy losses, but we are interested in energy arbitrage because it offers the potential for batteries to reduce carbon emissions. In a typical restructured wholesale electricity market, the wholesale electricity rate is determined by an auction system in which each power plant submits a bid indicating how many MWh they are willing to supply at various price levels. Then, subject to the transmission constraints, the least cost generators are called upon (i.e., dispatched) to produce electricity until supply equals demand. At each node in the transmission system, the market clearing price, also known as the locational marginal price (LMP), is determined by the marginal cost of supplying one more MWh of electricity to that node (Wolak 2021).

Figure 1 illustrates a hypothetical dispatch curve adapted based on the generation fleet of CAISO. Each bar presents a particular generation technology (e.g., solar, wind). The width of the bar measures the available generation capacity, and the height of the bar measures the marginal costs of the corresponding generation technology. The curve plots the average emissions intensity for each generation technology. In a perfectly competitive market, generators will bid at their marginal costs. The wholesale electricity price thus equals the marginal costs of the marginal generation technology that intersects with the demand curve.

Renewable energy resources such as solar and wind have near-zero marginal costs and are usually dispatched automatically. However, these intermittent energy sources only generate power when the sun shines or the wind blows. Wholesale electricity prices could be zero (or even negative) when solar or wind power is on the margin. However, when solar and wind generate less power and are no longer on the margin, the wholesale electricity price will be determined by generation technologies with higher marginal costs, such as natural gas. Differences in wholesale electricity prices create arbitrage opportunities for batteries.

As shown in Figure 1.1, with a high penetration of solar energy sources, batteries can charge during the middle of the day when the wholesale electricity price drops to zero. Then, as shown in Figure 1.2, the battery can discharge during evening ramps when the wholesale electricity price becomes higher, as open-cycle (i.e., simple-cycle) natural gas units are on the margin. As a result, the demand curve would shift from D1 to D2 in the middle of the day. As solar energy has zero carbon emissions, this increase in demand will not increase emissions. In the evening ramp, battery discharge can reduce the demand from D2 to D1. If batteries have a round-trip efficiency of 80%, then for every kWh charged into the battery, 0.8 kWh can be discharged. The discharge reduces the required electricity generation from open-cycle gas turbines and associated carbon emissions. The avoided carbon emissions are given by multiplying the discharged kWh with the emissions intensity (kg CO_2 per kWh) of the marginal technology (open-cycle).

This basic economic mechanism, where renewable energy is used to displace a dirtier source, can be applied to both CAISO and ERCOT. However, the magnitude of the emissions reductions may differ due to a number of reasons. First, the emissions reduction from energy arbitrage is determined by the marginal emissions during battery charging and discharging. Since solar and wind have near-zero emissions, if batteries are charged from these sources, the emissions reductions will be determined by the generation technologies used during battery discharging. For example, batteries can be used to displace coal-fired generators in ERCOT compared to natural gas generators in CAISO, leading to a greater reduction in emissions in ERCOT. Second, emission reductions can differ because different renewable energy sources have different probabilities of appearing on the margin. Energy arbitrage is most profitable when renewable energy sources are deployed on the margin, which occurs when renewable generation can meet local demand and is facing curtailments.[18] Because ERCOT has higher renewable curtailment rates than CAISO[19], a battery in ERCOT is anticipated to bring more emissions reductions than CAISO. Third, ERCOT and CAISO have different seasonal patterns in terms of electricity demand and renewable generation. As a result, emission reductions can also exhibit seasonal effects.

18. This can occur in two scenarios. First, renewable generation may be sufficient to meet system demand, resulting in the curtailment of excess renewable generation and a MEF of zero throughout the system. Second, renewable generation may meet local demand, but due to transmission congestion, it cannot be transmitted to meet demand in other regions. In this case, the local MEF will be zero.

19. According to ERCOT (2022) and CAISO (2023a), ERCOT curtailed 5% of wind generation and 10% of utility-scale solar generation in 2022, while CAISO's solar curtailment rate was around 5%.

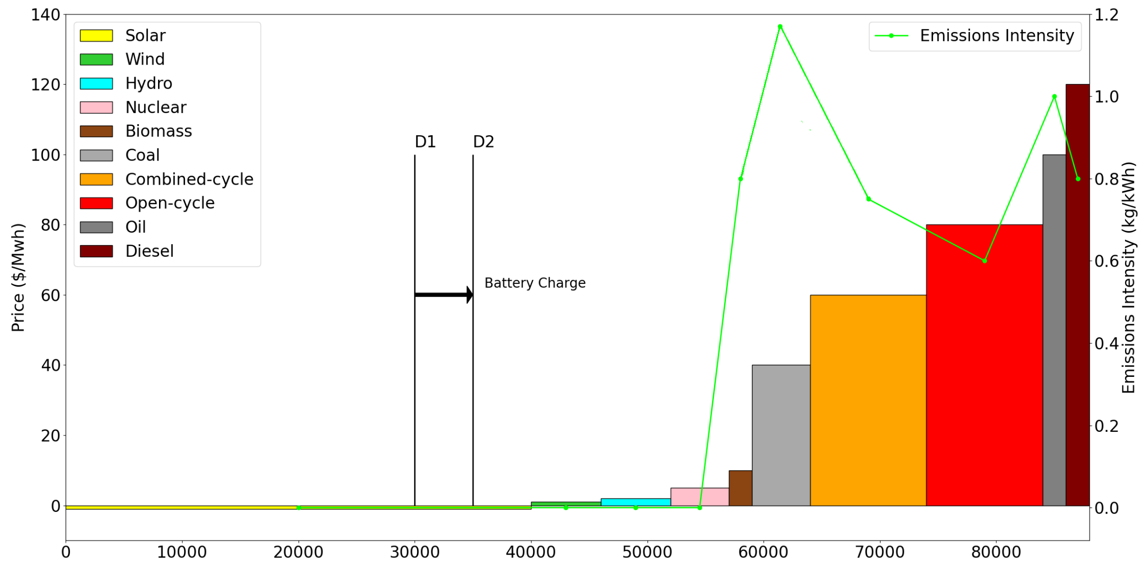


Figure 1.1: Hypothetical Dispatch Curve During the Middle of the Day

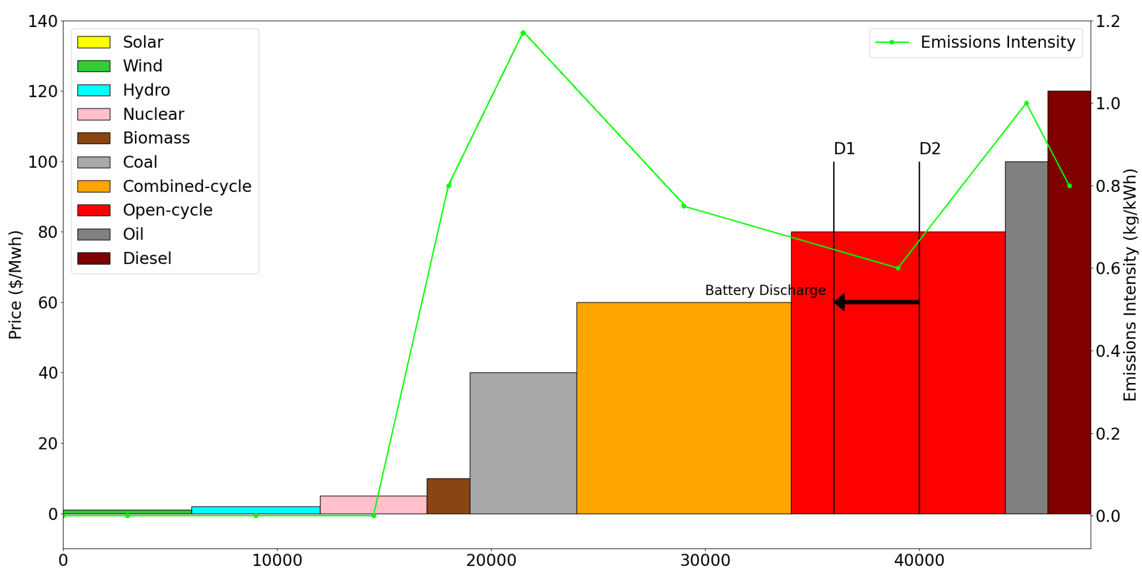


Figure 1.2: Hypothetical Dispatch Curve During the Evening Ramps

In our context, RTP has the potential to reduce carbon emissions in CAISO and ERCOT because these regions have high renewable penetration. The potential to reduce carbon emissions is greater when solar and wind are more likely to be on the margin. Generation capacities and market demand jointly determine whether solar and wind will be on the margin. Therefore, RTP has a more considerable impact on emissions during times with higher wind and solar output and lower market demand.

In areas with fewer renewables, or in hours where renewable generation has a low probability of being on the margin, RTP could increase emissions. For example, batteries could be used to charge at night when cheap coal units are on the margin and discharged when cleaner natural gas is on the margin.[20] As a result, the increased emissions during charging outweigh the avoided emissions during discharging. Combined with energy loss from batteries, the emissions could increase substantially.

1.4 Data

We collect data from several sources on generation, emissions, retail tariffs, demand profiles, and solar radiation. First, we utilize hourly emissions and generation data from the Environmental Protection Agency (EPA)'s Continuous Emissions Monitoring System (CEMS) for the years 2018, 2019, and 2020. CEMS includes data on hourly emissions and generation for all fossil fuel generators in the US with a capacity larger than 25 MW (EPA 2023a). To account for electricity generation from non-emitting sources, we complement the dataset with hourly data for wind and solar generations from each grid operator (CAISO 2023b; ERCOT 2023a).[21]

Second, we use real-world retail tariffs from the Utility Rate Database (URDB) to design representative retail tariffs for each jurisdiction. The URDB provides rate structure information for more than 3,700 US utilities (Open EI 2023). In each jurisdiction, we use

20. Hittinger and Azevedo (2015) shows that this is the case for most jurisdictions in the US.
21. Our dataset does not include hydropower, biomass, geothermal, and small fossil-fuel generators due to data limitations. A detailed discussion of the data limitations is provided in Section 5.4.

URDB to collect possible retail tariffs from local utility companies for medium commercial customers with a maximum demand range of 250 kW to 500 kW (Open EI 2023). To ensure that the collected retail tariffs are representative, we focus on large utility companies and active utility plans in 2020. In CAISO, we focus on the three major investor-owned utilities (IOUs): Pacific Gas and Electric (PGE), San Diego Gas and Electric (SDGE), and Southern California Edison (SCE). In ERCOT, we look at the ten largest utility companies by market share that have available information for their commercial plans (ElectricityMatch 2023).[22] In addition, following Borenstein and Bushnell (2022), we exclude any retail tariffs for specific customer types by removing any tariff with a name containing "agricultural," "rural," and "traffic." This leaves us with a more standard collection of retail tariffs for commercial customers.

The retail tariffs we collect are generally composed of three parts: a fixed charge, a demand charge, and a volumetric charge (typically TOU). Our analysis focuses on the TOU rate as it is adopted by most utilities for large commercial and industrial consumers and is a time-varying rate. For simplicity, we remove retail tariffs that contain tiered rates, as tiered pricing often lacks the time-varying feature of electricity pricing and does not justify the installation of batteries for energy arbitrage purposes.[23]

Third, we use the Commercial and Residential Hourly Load Profiles for all TMY3 (Typical Meteorological Year 3) locations in the United States provided by the Open Energy Data Initiative (NREL 2014). This dataset contains simulated hourly electricity consumption data for 16 commercial building types across the US, representing approximately 70% of all

22. The URDB only contains utilities that provide "bundled" services, which means the utilities that sell electricity also own and operate the distribution network (Borenstein and Bushnell 2022). However, in ERCOT, many retailers only provide the "energy" service. In this case, we manually collected retail tariff information for large utility companies that are omitted in the URDB: TXU Energy, Direct Energy, and Reliant Energy (ElectricityMatch 2023).

23. A tiered rate is a price structure in which one can use a certain amount of electricity at a lower price. Once a certain threshold is reached, a higher rate will apply. It is usually used to promote energy conservation and support low-income consumers (Borenstein 2016).

commercial buildings in the US (Deru et al. 2011). For expositional purposes, our analysis uses supermarkets as the representative demand profile. The demand profiles in different locations in a state are aggregated to the state level by taking the average. Appendix C presents the representative demand profile of supermarkets.

In addition, we use EnerNOC's (2013) Green Button database, which provides 5-minute electricity consumption data for 100 commercial/industrial sites across the US, to quantify the reliability of the synthetic data from the TMY3 dataset (EnerNOC 2013). The correlation between synthetic data and real smart meter data is 0.8548 for supermarkets. The results (see Appendix C) suggest that the synthetic demand profiles can reasonably reflect real-world data.

Fourth, we use solar radiation data in large population centers from the TMY3 dataset to calculate the average energy output of solar panels (NREL 2014). The TMY3 dataset provides solar radiation information for 1,020 locations throughout the US. For simplicity, in each region, we use the average solar radiation in the three largest cities in California and Texas to calculate the energy output from solar. The assumption is reasonable because most commercial BTM storage systems are located in these large population centers (CPUC 2018a).

1.5 Methodology

We use the Distributed Energy Resources Customer Adoption Model (DER-CAM) to investigate the impact of RTP and carbon tax on the GHG emissions resulting from solar plus battery systems. DER-CAM is a decision support tool developed by Lawrence Berkeley National Laboratory (LBNL) to make optimal operation and investment decisions for DER technologies (LBNL, 2020). The optimization program can determine the optimal charge and discharge decisions that maximize customer bill savings with exogenous DER capacities, subject to several financial and technological constraints. In addition, it can simultaneously solve the optimal investment and operation decisions for solar and storage. Section 1.5.1 illustrates how DER-CAM solves the optimization problem.

For a given demand profile and retail tariff design, we utilize DER-CAM to simulate the optimal operation and investment decisions for DER technologies and account for regional solar radiation, DER investment costs, and technological characteristics. Then, we use estimated MEFs to understand the environmental outcomes of RTP and carbon taxes compared to a more traditional TOU pricing structure. We first consider the case with exogenous solar and battery capacities. This allows us to isolate the impact of retail tariffs and carbon tax on carbon emissions resulting from charge and discharge decisions. Then, we simultaneously solve the operation and investment decisions to understand how retail tariff designs and carbon taxes would affect carbon emissions in the long run.

To understand how results could vary with generation mixes, our study covers CAISO and ERCOT, two of the leading jurisdictions in terms of renewable generation in the US (NREL 2020). In 2020, 37% of the energy consumed in CAISO came from natural gas, which generally served as the margin fuel. Solar and wind constitute 13% and 11% of energy, respectively (CAISO 2023a). In ERCOT, natural gas represented 46% of the energy generated in 2020, followed by wind (23%) and coal (18%) (Potomac Economics 2023b).

Renewable energy resources in CAISO and ERCOT have frequently been curtailed due to oversupply or local system congestion. According to EIA (2021a), in 2020, around 5% of total solar generation is curtailed in CAISO, within which 31.15% is system-wide curtailment due to oversupply. In ERCOT, 5% of all wind generation and 10% of solar generation were curtailed in 2020, mainly due to local congestion (Potomac Economics 2023b). As a reference, the Midcontinent Independent System Operator (MISO) has a 5% wind curtailment rate as compared to total generation and wind can appear on the margin for over 40% of the time

(Li et al. 2017). The results suggest that wind and solar are frequently on the margin and can significantly affect system MEFs.

It is important to acknowledge that we assume that the demand profiles remain constant as we adjust the retail tariff. We carry out robustness checks to evaluate the implications of this assumption. The details of this analysis are described in Section 1.7.1.

1.5.1 Optimization Program

DER-CAM solves the optimal investment and operation decisions by minimizing total costs, subject to several technological constraints.[24] Total costs include electricity bills and technology costs (investment and operation costs) for solar and storage systems. The electricity bills contain fixed and variable charges, minus the energy credits earned from selling excess solar power back to the grid. A detailed discussion on how customers are compensated for exporting excess solar power is discussed in Section 1.5.5.

In the exogenous setting, the capacities for solar and battery storage are predetermined, whereas DER-CAM chooses the optimal charge and discharge decisions to maximize customer bill savings. In the endogenous setting, DER-CAM solves both the investment and operation decisions for the solar plus storage systems. The solar/storage capacity configuration is chosen to obtain a global optimization (minimize total costs) based on optimized charge and discharge decisions. This optimization problem is formulated in DER-CAM as a Mixed Integer Linear Program (Cardoso et al. 2017).

For simplicity, DER-CAM solves the problem based on hourly demand profiles represented by three day-types (weekdays, weekends, and high-demand days) for each month of a representative year. As a result, our primary analysis only captures the average trend of RTP and

24. See Appendix B and Boampong and Brown (2020) for additional details on DER-CAM.

omits changes within hours or across days for a given month. It is important to note that this will reduce the variance of RTP, leading to underestimated arbitrage opportunities. Consequently, it could lead to underestimated battery installation and energy arbitrage incentives. As a robustness check, we design an algorithm based on the same objective function and constraints as the exogenous case to understand how our results could differ if we allow RTP to vary hourly and daily (see Section 1.7.2). Given the complexity of the endogenous case, our algorithm is designed exclusively for the exogenous scenario. To maintain consistency across both situations, we employ DER-CAM as our benchmark algorithm for both cases.

While solving the optimization problem, DER-CAM uses MEFs to calculate the total carbon emissions for each retail structure, which is calculated as follows:

$$Emission = \sum_{m}\sum_{d}\sum_{h} D_{mdh} MEF_{mh} \tag{1.1}$$

where m, d, and h represent month of the year, day type, and hour of the day, respectively. D_{mdh}, therefore, represents the electricity demand for a specific month m, day type d, and hour h. Section 1.5.4 provides a detailed discussion on how MEFs are estimated.

1.5.2 DER Technologies

This section outlines the basic features of solar and battery technologies in our analysis. Following Boampong and Brown (2020), we assume that the battery has a round-trip efficiency of 0.8 (i.e., a 20% of energy loss between charge and discharge), a charge and discharge rate of 0.3 (i.e., a maximum of 30% of total capacity can be charged and discharged per hour). In addition, we assume that the battery has a life span of 10 years and solar photovoltaic has a life span of 25 years, reflecting the most cost-effective battery technology (Mongird et al. 2019).

The costs of solar and storage have dropped significantly in the past ten years. Following Cardoso et al. (2017) and IRENA (2017), we assume that the battery has a capital cost of

$260 per kW, which reflect a base capital cost of $560 per kW and a government subsidy of $300 kW (from SGIP).[25] We follow Feldman et al. (2021) and assume that solar PV has a variable cost of $1,750 per kW. In addition, we follow Mongird et al. (2019) and assume that battery has annual maintenance costs equal to 0.3% of the total capital expenditure, while solar PV has annual maintenance costs equal to 0.5% of the total capital expenditure. In addition, the discount rate is assumed to be 3%. Different assumptions on technology features, capital costs, and discount rates could slightly alter the investment decisions for solar and storage systems. However, the qualitative conclusions are likely to persist.

1.5.3 DER Capacity

In our exogenous setting, consumers choose the optimal charge and discharge decisions with predetermined solar and storage capacities. We must, therefore, assume an exogenous amount of solar plus storage capacities to conduct the analysis. Consumers may install solar PV or a solar plus storage system for various reasons, such as managing maximum demand[26], maximizing electricity bill savings, or using storage as an emergency backup during power outages (Boampong and Brown 2020).

Solar PV has been shown to achieve a high net present value under commonly employed compensation policies. In 2020, the payback period for solar PV systems was around six years in the US (SEIA 2022). As a result, for large electricity consumers, the size of solar PV is mainly constrained by the roof space. The average roof space size for a supermarket is approximately 4,000 square meters, which permits a maximum PV system of 599 kW (Kurdgelashvili et al. 2016). We assume that consumers will install the maximum PV capacity in the exogenous setting.[27]

25. While ERCOT does not have a state-wide subsidy for BTM storage, we assume the same government subsidy to CAISO and ERCOT to ensure parity.

26. Customers can use a battery system to reduce maximum demand through load shifting and reduce demand charges.

27. Boampong and Brown (2020) assume that customers will choose a PV capacity that can offset 50%

There is no simple way to determine the exogenous battery capacity, as different consumers may install batteries for different reasons. Following Boampong and Brown (2020), we determine the exogenous battery capacity by assuming that consumers will choose a storage capacity that can completely flatten the demand profiles in hours where utility purchase is necessary. We first calculate the solar generation in each hour based on our exogenous solar capacity. Then, we calculate the average net load $\bar{L}$ and the net load in each hour with no solar export L_t. The battery capacity equals the sum of the positive deviations between L_t and $\bar{L}$. The exogenous capacities for solar and battery are shown in Table 1.

	CAISO	ERCOT
Solar PV (kW)	599	599
Battery Storage (kW)	418	429

Table 1.1: Exogenous Capacity for Solar PV and Battery Storage

1.5.4 Marginal Emissions Factor

The marginal emissions factor (MEF) measures the carbon abatement potential from changes in electricity generation. In particular, MEFs measure the increase in emissions resulting from a 1 MW increase in market demand (or electricity generation) and can be used to evaluate energy efficiency policies and behavioral changes that shift energy load.

In the literature, MEFs are measured with various time frames. For example, Graff Zivin et al. (2014) estimate MEFs for each hour of a day for the entire sample period (three years). To capture potential seasonal effects, we estimate month-hour MEFs for each hour of the day and month of the year. Following Graff Zivin et al. (2014) and Callaway et al. (2018),

of their peak day usage. Their resulting exogenous capacity is similar to what we assumed. For example, following their assumption, supermarkets in California and Texas will install a solar PV of 531 kW and 601 kW, respectively. Our results are robust to different assumptions of PV capacity.

we estimate the following model for each region:

$$E_t = \sum_{m=1}^{12}\sum_{h=1}^{24}\beta_{hm}\cdot HOUR_h\cdot MONTH_m\cdot G_t + \sum_{m=1}^{12}\sum_{h=1}^{24}\alpha_{hm}\cdot HOUR_h\cdot MONTH_m + \varepsilon_t \quad (1.2)$$

where E_t and G_t measure hourly emissions and hourly electricity generation, respectively. As described in Section 4, the emissions data from the CEMS only contains carbon emissions from fossil fuel generators located within the jurisdiction territory with a generation capacity of 25 MW and above. G_t is the hourly generation from these fossil fuel generators, plus renewable generation from solar and wind sources located within the jurisdiction territory . $HOUR_h$ and $MONTH_m$ are dummy variables for hour h of the day and month m of the year, respectively. The fixed-effects term α_{hm} captures the average levels of emissions observed in hour h and month m. The month-hour MEFs are captured by β_{hm}. We use generation rather than total electricity demand because our emissions data do not entirely match aggregate demand. For example, by using the CEMS data, we ignore emissions associated with energy imports.

Due to data availability, our approach has several limitations. First, the hourly generation contains only thermal, solar and wind energy sources, which excludes other marginal fuel types such as small fossil fuel, biomass, and hydro. As presented in Siler-Evans et al. (2012), biomass and small fossil fuel plants only represent a small percentage of the overall generation fleet. For example, in Texas, biomass generation accounts for only 0.1% of the total generation, whereas small fossil fuel plants excluded by the CEMS take 1.4%. In CAISO, these excluded plants account for 2.8% of total generation. In addition, biomass power is usually used as baseload power (Matek and Gawell 2015). Therefore, these plants have minimal impact on the MEFs. As discussed in Siler-Evans et al. (2012) and Callaway et al. (2018), assessing hydropower is particularly challenging. For example, a battery discharge will reduce hydro generation when hydropower is on the margin. In this case, the MEF will be estimated as zero. However, a hydro reservoir could reserve the water for later use instead of spilling the additional water. As a result, instead of reducing zero emissions at hour A, the battery discharge at hour A may reduce future emissions at hour B. Depending on how hydropower operates and when hydropower is on the margin, hydropower could have different effects on the MEFs.

Second, we assume that all consumption in a region is met by generation units from the same area, which rules out energy exchange across regions. For example, since CAISO imports energy from neighboring areas (with coal-fired power plants) to meet demand, the MEFs during peak demand hours could be underestimated.

Third, we assume that there are no line losses. Line losses account for approximately 9% of the total generation (Graff Zivin et al. 2014). By excluding line losses from the analysis, we could slightly underestimate the MEFs because we measure the increase in emissions resulting from a 1 kW generation instead of a 1 kW consumption. Because line losses can vary by hours and locations, accounting for line losses can be challenging.

Our methodology differs from previous studies (e.g., Siler-Evans et al. 2012; Graff Zivin et al. 2014; Callaway et al. 2018) in two ways. First, to understand the effects of RTP in greater time granularity, we estimate hour-month MEFs instead of annual or seasonal MEFs. Second, we estimate MEFs in an environment where renewable energy sources could be on the margin, whereas previous studies assume that renewable energy sources rarely appear on the margin. However, with the significant deployment of renewables and developments of the transmission system and dispatching mechanism, renewable energy sources have been deployed frequently on the margin (Li et al. 2017). For example, between 2014 and 2016, the wind was on the margin for more than 40% of the time in MISO (Li et al. 2017). In CAISO and ERCOT, renewable energy sources have been curtailed frequently, indicating their presence on the margin (CAISO 2023a; Potomac Economics 2023b). Omitting these energy sources will significantly overestimate the MEFs in hours during renewable generation.

For example, if only emitting generation sources are used to estimate the MEFs in CAISO, the MEFs are mostly constant across hours because only natural gas generators are used to meet marginal demand. We find that this can lead to an 60% overestimation of MEFs in the middle of the day in spring.

Our estimates of the MEF are shown in Figures 1.3 and 1.4. The MEFs shown in the figures are measured as the change in carbon emissions (kg) in response to a change in electricity generation (kWh). Figure 1.3 shows the estimated MEFs of CAISO in each month-hour of a representative year. In CAISO, peak electricity demand occurs in summer, and MEFs in the summer months are higher as peaking natural gas plants generally serve the margin. In spring and summer, renewable energy sources, especially solar, play an essential role in electricity generation in CAISO (CAISO 2023a). As a result, MEFs during solar generating hours are considerably lower in the spring months because system demand is relatively lower in spring. Therefore, solar has a greater chance of appearing on the margin in spring than in summer. The high-demand hours in CAISO occur from 4 PM to 9 PM, and the MEFs are generally higher during this period. Therefore, in the spring months, storage has the potential to reduce emissions by shifting clean energy to high-demand hours. However, in other months of the year, the relatively flat MEFs provide minimal opportunities for emissions reduction.

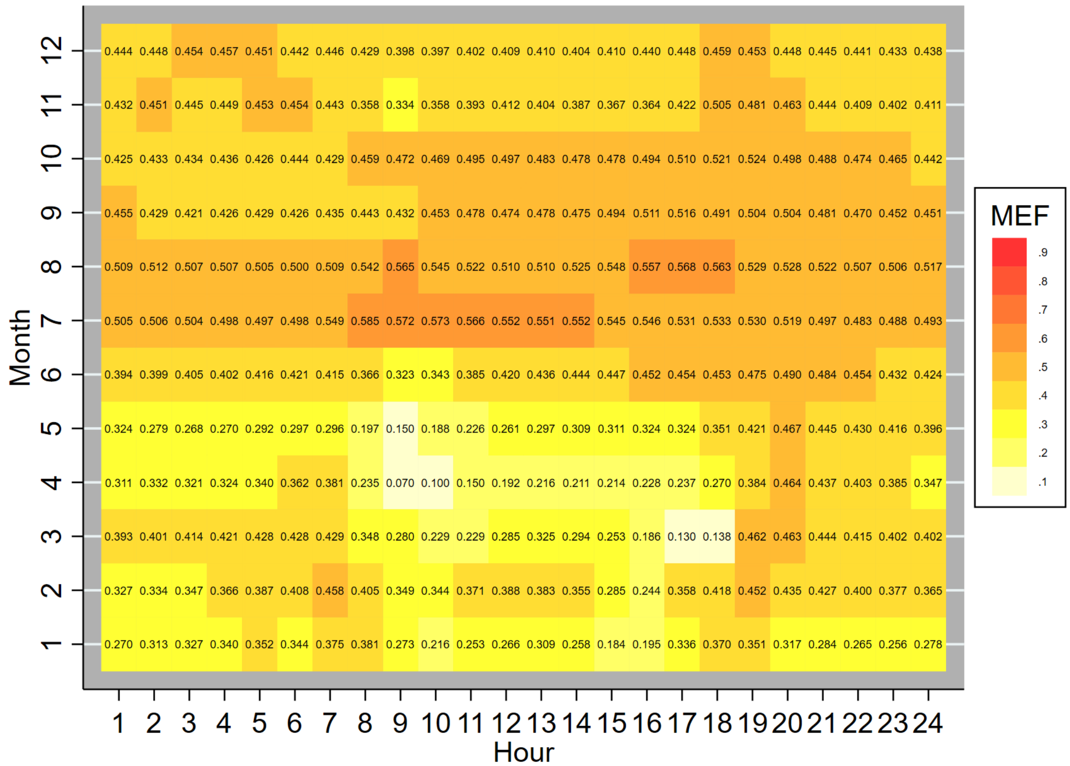


Figure 1.3: Month-Hour MEFs for CAISO (kg CO_2 per kWh)

Figure 1.4 shows the estimated MEFs of ERCOT in each month of a representative year. ERCOT reaches peak electricity demand during winter due to prevalent electric heating and relies on coal plants to meet peak demand, resulting in very high emissions during the winter months (White et al. 2021). During winter, MEFs are higher during the off-peak period than the peak period, as coal-fired generators are used for baseload generation, whereas cleaner natural gas generators are used to meet peak demand. In most of the other months, MEFs are affected by wind generation at night. In these months, MEFs showed higher variances than CAISO, which leaves more potential for emissions reduction through load shift.

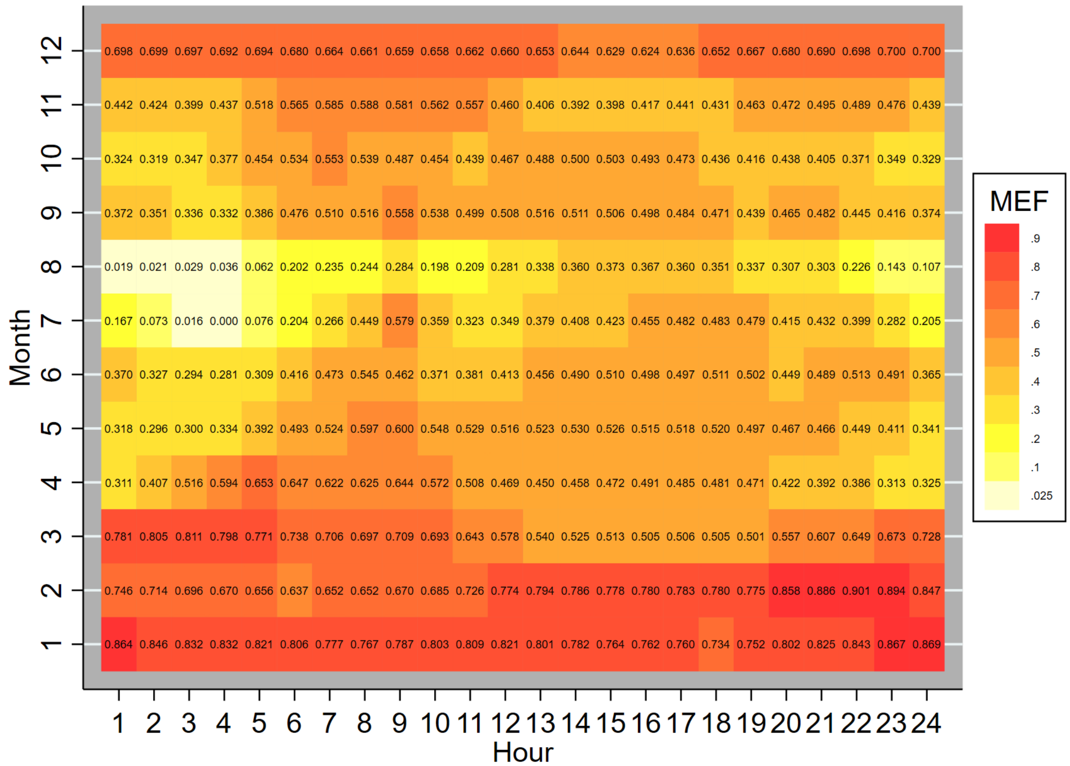


Figure 1.4: Month-Hour MEFs for ERCOT (kg CO_2 per kWh)

1.5.5 Tariff Design and Solar Compensation Policy

Solar Compensation Policy

Most states have implemented a net-metering policy in the US to encourage solar PV adoption (Brown and Sappington 2017b). Under net metering, consumers can export excess solar energy to the utility in exchange for energy credits. These energy credits can be used to offset electricity purchases from the same TOU period when the export occurs, usually on a 1-to-1 basis (at the prevailing retail rate). Different utilities have different policies on how long these energy credits can be stored. For example, energy credits can be stored for 12 months in California (CPUC 2022). In contrast, energy credits earned by exporting solar energy in a month cannot be carried over to the next month in Texas (Quick Electricity

2022).[28] When the total solar export exceeds the total utility purchase, any surplus export will not be compensated or will be compensated at a lower rate.[29]

To ensure comparability, we establish the same compensation rule for the TOU rate in ERCOT and CAISO. We assume that solar export is compensated for at the retail rate in the corresponding TOU period. In addition, the energy credits can be stored for the entire representative year. Lastly, following the FERC order 2222, we assume that net surplus export can be exported to the wholesale market and earn the wholesale rate at the corresponding hour (FERC 2021). Our analysis uses the retail net-metering policy as the benchmark case.

Retail Tariff Designs

The representative retail tariffs are designed as follows. We start by collecting the retail tariffs in a region and extracting the fixed and demand charges from each retail tariff. Then, we calculate the total electricity bill for our representative customer for each retail tariff we collected.[30]

The TOU rates in our analysis are designed such that a utility can recover the average revenue made by the real-world retail tariffs from the representative customer, absent any DER investment. We create two representative TOU rates for each demand profile with peak-to-off-peak ratios equal to 2 and 5, respectively. For simplicity, the TOU rates in our analysis contain a peak and an off-peak period. To determine the peak period for each region

28. Texas does not have a state-wide net-metering policy, but many utilities offer solar buyback plans that work the same as net-metering.

29. Utilities in Texas do not offer compensation for this net surplus export. In California, this net surplus will be compensated for at the net surplus compensation rate, calculated based on the average energy market rate over the past 12 months. This rate is generally less than 4 cents per kWh in California. In general, any excess solar generation above consumer demand is not profitable.

30. We first calculate the monthly kWh consumption for each TOU period and the monthly maximum demand based on the representative demand profile. Then, we calculate the monthly volumetric charges by multiplying the kWh consumption by the corresponding rates and monthly demand charges by multiplying the maximum demand by the demand charge rate. Lastly, we add the monthly fixed payment.

in our study, we use K-mean clustering[31] to cluster demand into two groups using the system demand profile for CAISO and ERCOT during weekdays, respectively. The results indicate that the peak period in CAISO is between 4 PM and 9 PM (weekends excluded), whereas the peak period in ERCOT is between 1 PM and 6 PM (weekends excluded).[32]

Given the peak and off-peak periods, the TOU rates can be calculated with the following equations

$$TotalBill = D_{peak} \cdot rate_{peak} + D_{off} \cdot rate_{off} + fixed \tag{1.3}$$

$$rate_{peak} = s \cdot rate_{off} \tag{1.4}$$

whereas D_{peak} and D_{off} are kWh consumption during peak and off-peak periods, respectively. $rate_{peak}$ and $rate_{off}$ are the energy rates during the peak and off-peak periods, respectively. s is the peak-to-off-peak ratio (2 or 5). $fixed$ is the fixed charge, which is calculated taking the average of all fixed charges of the collected retail tariffs.

The RTP in our paper is designed as the average LMP for all trading hubs in the day-ahead market in a region, plus a fixed charge. The LMP of a trading hub is the average of all LMPs in the corresponding trading zone. The fixed charge ensures that the utility company recovers the exact costs as the TOU rates, absent any DER investment. We calculate the fixed charge by subtracting the total hourly electricity charges from the total electricity bill. Based on our retail tariff designs, absent any DERs, the total electricity bills are identical across: (i) the observed real-world tariff, (ii) the TOU tariff, and (iii) the RTP tariff. This establishes an equitable starting point for comparing TOU and RTP.

31. K-mean clustering is a common method for dividing data into smaller groups based on a similarity measure (Green et al. 2014). In our setting, the peak and off-peak periods are determined so that the distance between the hourly demand and the average demand of a period is minimized for each hour within that period.

32. Our peak period hours are similar to the peak period hours chosen by the real-world utilities. For example, three major utility companies in California offer TOU rates with peak periods between 4 PM and 9 PM. The peak period of the ERCOT region generally spans from 1 PM to 7 PM, but may vary with the season.

It is important to note that our TOU rates are constructed using the prevailing retail prices that include demand charges. In the RTP structure, these charges are lumped into fixed charges. Although it will not affect the charge and discharge decisions for batteries in our exogenous case, it could affect the compensation rate of solar and investment decisions for DER technologies. In particular, the solar compensation rate under the TOU rates could be overestimated, leading to higher investment levels.

Carbon Taxes

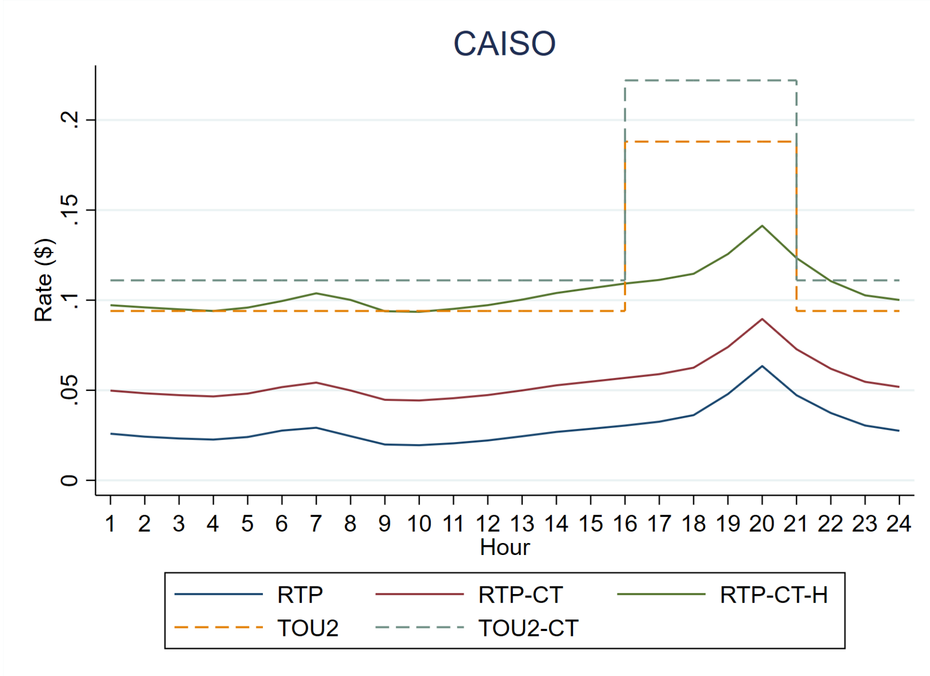
In order to examine the effects of carbon taxes on the environmental outcome brought about by solar plus storage systems, we include carbon taxes on each retail tariff we described above. For the TOU rate, we calculate the carbon emissions generated from each period and multiply them by the corresponding carbon price to obtain the total carbon taxes for each period. Then, we calculate the per kWh carbon costs by dividing total carbon taxes by the kWh consumption for each TOU period. Lastly, we add the per kWh carbon costs to the existing peak and off-peak period energy rate to obtain the new TOU rates with carbon taxes.[33] For the RTP, we multiply the carbon price by the MEF for each hour in each month and add this per kWh carbon cost to the existing RTP rate.

We assume two levels of carbon tax: a normal level and a high level. The levels of carbon tax are determined by the social cost of CO_2 in 2020, estimated at IWG (2021). The normal level carbon tax is \$51 per metric ton of CO_2, which is the average social cost of CO_2. The high level of carbon tax is \$152 per metric ton of CO_2, which is the estimate of the social cost of CO_2 in the 95th percentile.

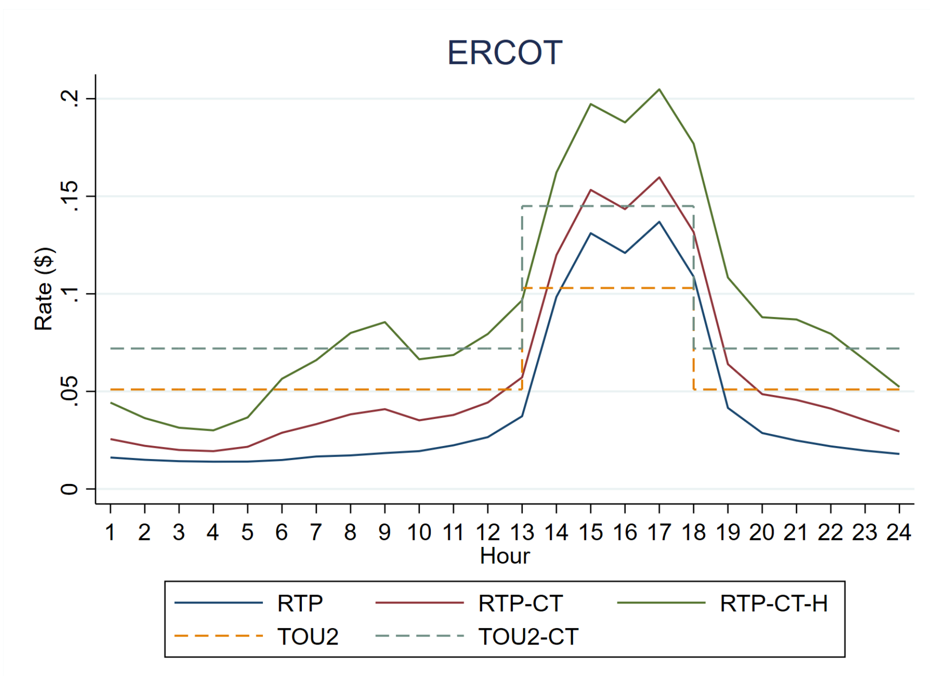
33. For example, suppose a TOU tariff has two periods, peak and off-peak. Without a carbon tax, the peak and off-peak rates are p_1 and p_2 ($p_1 > p_2$), respectively. Suppose that the carbon tax is c\$ per kg, the MEF during peak and off-peak periods are e_1 and e_2, respectively. Because the MEF measures the increase in emissions resulting from the increase in electricity demand. The TOU plus carbon tax rates during the peak and off-peak periods will be $p_1 + e_1 * c$ and $p_2 + e_2 * c$, respectively. In this setting, as long as $p_1 + e_1 * c > p_2 + e_2 * c$, the batteries will charge during period 1 and discharge during period 2 to maximize arbitrage gains.

Our carbon tax designs assume that the current tariff designs do not feature a carbon pricing policy. As California has a carbon cap and trade system, the current tariff design, absent carbon taxes, already includes carbon pricing, since energy sellers tend to "pass through" most of the carbon costs to end-users (Fabra and Reguant 2014). As a result, in CAISO, the carbon tax level in our analysis could be higher than the actual social cost of carbon, and the effects of carbon taxes on emissions reductions could be overestimated. However, the current carbon pricing policies (e.g., cap and trade) tend to underestimate the cost of carbon significantly. For example, in 2020, the estimated social cost of carbon is around \$50, but the carbon allowance price in California is around \$17 (CARB 2022). Thus, our rate designs should reflect the social cost of carbon reasonably well.

Figure 1.5 shows the final retail tariffs (with different levels of carbon tax) analyzed in our paper. As an illustration, we only show the TOU2 rate (the TOU rate with a peak-to-off-peak ratio of 2). Compared with ERCOT, the average TOU rates in CAISO are much higher, reflecting the high energy costs in CAISO. The overall pattern of RTP with different levels of carbon taxes is similar in CAISO because of a high correlation between the MEFs and the RTP. As a result, the arbitrage opportunities with or without carbon taxes do not differ significantly. In contrast, carbon taxes could greatly impact the charge and discharge patterns in ERCOT due to higher variances of MEFs. In addition, the considerable divergence in the RTP indicates that the battery can be more profitable in ERCOT. Additional information on retail tariff designs is shown in Appendix D.



(a) CAISO



(b) ERCOT

Figure 1.5: Retail Tariff Designs
Notes: RTP, RTP-CT, and RTP-CT-H stand for RTP with no, normal, and high carbon tax levels, respectively. TOU2 and TOU2-CT are TOU rates with no and normal carbon tax levels, respectively. For expositional purpose, we do not show TOU2-CT-H, TOU5, TOU5-CT, TOU5-CT-H on the graph.

1.5.6 Summary of Methodology

We consider two retail rate designs: RTP and TOU. We compare the environmental outcomes of RTP with the TOU rate to investigate the effects of retail tariffs on carbon emissions and how the results would vary with various settings of carbon tax. Under each tariff structure and carbon tax setting, we consider three solar and storage cases: a benchmark case where there is no DER technology, a solar-only case, and a solar plus storage case. The outcome differences between the RTP and TOU case capture the effects of different retail rate tariffs on DERs. The differences between the solar-only and solar-plus-storage cases capture the storage-induced carbon emissions. The different tariff structures and variations analyzed in our study are summarized in Table 1.2.

Regions:	CAISO, ERCOT
Tariff Structure:	RTP, TOU
Carbon Tax Level (\$/ton CO_2):	\$0, \$51, \$152
Solar & Storage Installation:	No solar and storage, solar only, solar plus storage

Table 1.2: Summary of Variations

Throughout the analysis, we use supermarkets as the representative demand profile. However, our results are robust to alternative demand profiles. To further illustrate, we first consider the TOU rate. With pre-determined solar and battery capacities, demand profile will not affect the charge and discharge decisions for batteries. This is because, under net metering, customers are compensated at the prevailing retail rate, meaning that exporting energy to the grid has the same financial effect as using the energy on-site.[34] In this circum-

34. Under net metering policy, customers can export energy at time t_1 and use the credit to offset energy use at t_2, as long as both t_1 and t_2 belong to the same period. Essentially, solar generation at any point during a period can be considered to be generation for the entire period. This is true as long as solar generation during a period does not exceed the total consumption for that period.

stance, customers will charge batteries during off-peak periods and discharge them during peak periods, regardless of the demand profile. For the same reason, only the aggregate energy consumption in each TOU period (and the peak-to-off-peak demand ratio) will affect the investment decisions for solar and battery in the endogenous case. This is because once self-generation completely offsets self-energy use in a period, additional energy exports will not be compensated at the prevailing retail rate.[35] This constraint can be binding in the endogenous case, leading to different solar and battery investment decisions.[36]

In terms of RTP, demand profiles do not influence battery charge and discharge decisions in the exogenous case. Similarly to the TOU case, this is because the solar compensation rate is the same as the retail rate under RTP. Batteries will charge when the energy rate is low and discharge when the energy rate is high, regardless of the demand profile. In the endogenous case, since the solar compensation rate always equals the RTP[37], even if the energy export exceeds the energy usage at the corresponding hour, the investment decisions for solar and batteries will also remain unaffected by the demand profile.

It should be noted that adding carbon taxes to the RTP could affect the charge and discharge decisions of the battery because the solar compensation rate (RTP) will differ from the avoided energy rate when self-use (RTP+CT). However, this will only occur with a sufficiently high carbon tax level that fundamentally alters the ordinal sequence of the energy rate. For example, if the lowest rate changes from 3 AM to 2 AM. Similarly, adding carbon

35. Refer to Section 1.5.5 for the compensation policy regarding surplus solar exports.

36. Consider two extreme conditions: Customer A, who only uses electricity during off-peak periods, and Customer B, who only uses electricity during peak periods. Suppose that solar power only generates electricity during off-peak periods. Even if solar panels and batteries are sufficiently cheap, Customer A will only install solar panels. The solar capacity is determined by the total energy usage of this customer. On the other hand, Customer B could install both solar and battery systems and use the battery to shift energy from off-peak periods to peak periods. When solar panels and batteries are sufficiently cheap, this customer will install capacities such that the energy shifted to the peak period just offsets his total energy usage in the peak period.

37. Under RTP, solar energy is compensated at the RTP rate when there are no surplus exports. When energy exports exceed consumption, customers can sell the surplus solar energy to the grid at the wholesale electricity price, as stipulated by FERC Order 2222.

taxes to TOU tariffs may affect charge and discharge decisions only if it fundamentally changes the TOU structure such that the energy rate during the off-peak period is higher than the peak period, which is unlikely to occur.

Lastly, batteries will exhibit identical charge and discharge patterns under TOU in the exogenous case, regardless of their carbon tax levels. This is because adding a carbon tax to the TOU will only affect the peak and off-peak energy rates, and batteries will still charge during off-peak periods and discharge during peak periods. Therefore, only the base TOU case is presented in the results to avoid redundancy.

1.6 Results

1.6.1 Exogenous Results

This section presents the results with exogenous solar and storage capacities specified in Section 1.5.3. This allows us to focus on the charge and discharge decisions of the storage systems and isolate the environmental effects resulting directly from battery operations. As our main qualitative results are robust to demand profiles of different customer types, we use supermarkets as the representative demand profile.

Figure 1.6 presents the results by retail tariffs during peak days. A positive/negative kWh indicates that the battery is charging/discharging at the corresponding hour. The vertical lines show the TOU peak periods. Under TOU pricing, customers will follow the same charge and discharge pattern regardless of the peak-to-off-peak rate ratios to maximize bill savings. Therefore, only one TOU rate is presented in the figure. As shown in Figure 6, batteries will be charged to maximum capacity under TOU rates before entering the peak period, as this is the only arbitrage opportunity under the TOU pricing. The battery will start to release power as soon as the peak period starts to minimize energy storage losses.[38]

Under RTP, batteries will target the RTP rate ramps. For example, the batteries in both CAISO and ERCOT tend to discharge in the mornings and evenings when the RTP rate increases. When there is a carbon tax, batteries will adjust the charge and discharge pattern in part on the basis of the MEFs. This will reduce CO_2 emissions in hours where the RTP rate and the MEFs are less correlated.

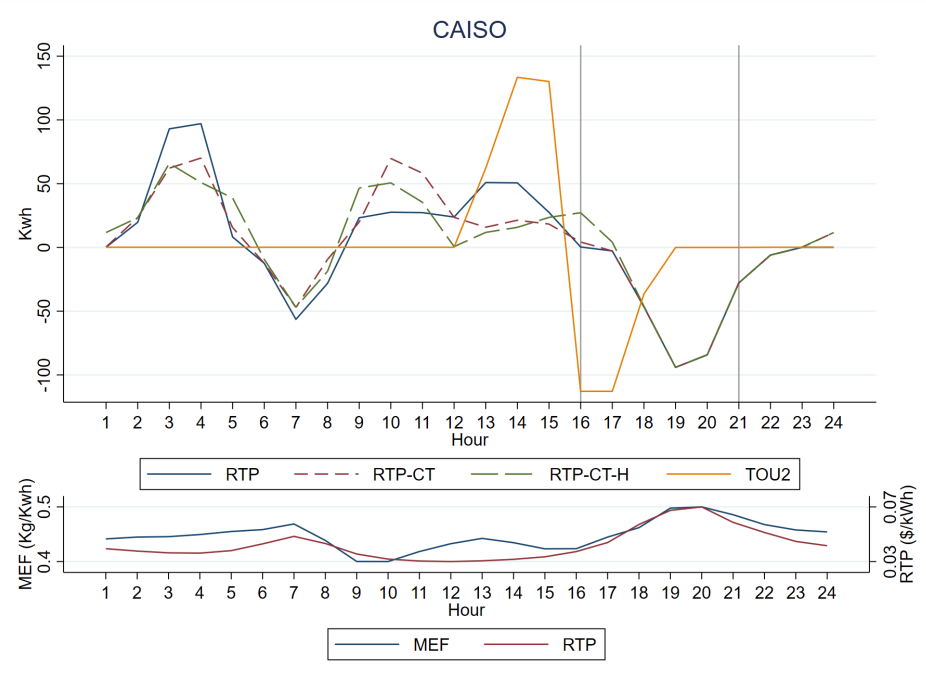
Figure 1.6(a) presents the battery charge and discharge pattern for CAISO. Under the TOU rate, batteries are charged to maximum capacity at 3 PM before entering the peak period. The battery will start to release power as soon as the peak period starts to minimize energy storage losses. Under the RTP rate, batteries will target the two RTP rate ramps in the morning (7 AM) and evening (19 PM and 20 PM). When there is a carbon tax, customers are discouraged from charging batteries overnight because MEFs are relatively high (due to baseload natural gas units) despite low RTP rates since it is less profitable to charge overnight as compared to the no carbon tax setting. Higher carbon taxes further reduce the incentive of overnight charging, but a normal carbon tax is sufficient to capture most of the reduction.

Compared to CAISO, the majority of ERCOT's renewable generation comes from wind energy sources, which produce most of the energy overnight (1 AM to 4 AM). As a result, MEFs in ERCOT do not correlate with TOU peak hours or the RTP rate during the day. Figure 1.6(b) presents the battery charge and discharge decisions for supermarkets in ERCOT. The early TOU peak period overlaps with solar generation hours. During these hours, power generated from solar is used for both self-consumption and battery charging, and excessive power will be discharged during late peak hours. Similarly, the RTP peak overlaps

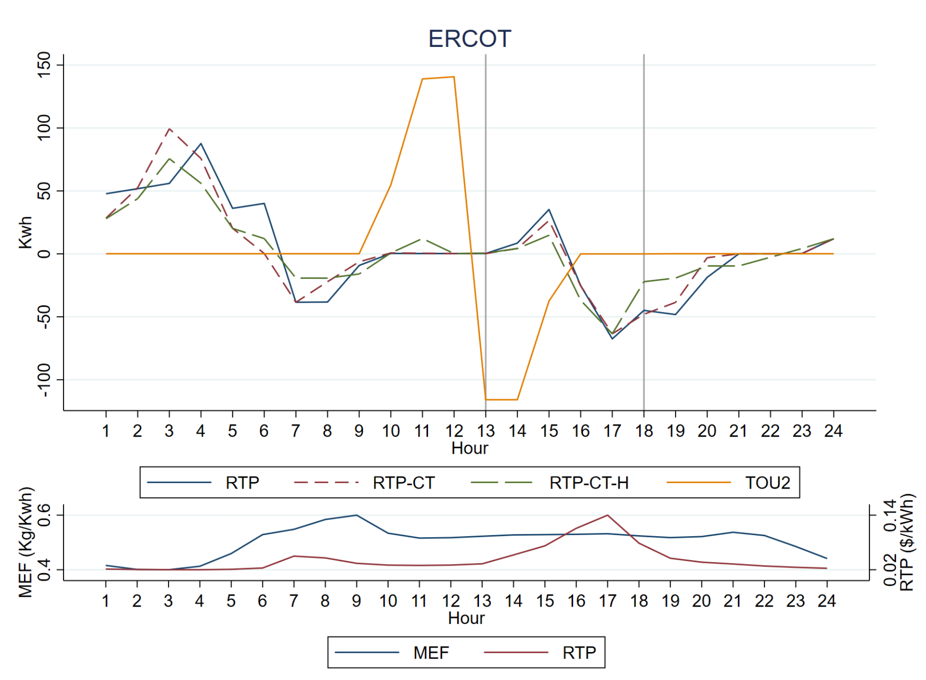
38. The energy losses (or "self-discharge") identified here occur when energy stored in batteries is reduced due to internal chemical reactions. Unlike the energy losses represented by the round-trip efficiency (which occurs during charge and discharge), it represents an energy loss during storage. It is expressed as a percentage of the charge lost over a certain period (Divya and Østergaard 2009).

with solar generation under the RTP rate, leading to delayed battery discharge. In addition, lower RTP rates and lower emissions intensity from wind generation overnight encourage overnight battery charging and discharging during early mornings.

A major difference between CAISO and ERCOT is that solar produces more energy during the peak period in ERCOT. As a result, the residual demand (demand minus on-site solar generation) is lower in the ERCOT, leading to lower battery discharges at the evening ramp. This implies a potential substitution effect between solar PV and batteries in the ERCOT.



(a) CAISO



(b) ERCOT

Figure 1.6: Battery Charge and Discharge Decisions

The environmental outcomes for CAISO and ERCOT under different retail tariff designs are presented in Table 1.3. All percentage changes are relative to the solar-only case, which measures the environmental effects of batteries. We do not present the results for TOU-CT because the batteries will operate the same under TOU, regardless of the rate difference between peak and off-peak periods. Under the current (TOU) retail rate design, we find that adding on storage to an existing solar-only system tends to increase emissions, which is in line with previous studies (e.g., Hittinger and Azevedo 2015). As MEFs during charge and discharge are similar, the increases in emissions can be mainly attributed to the 80% round-trip efficiency. Compared to the TOU rate, we find that RTP can reduce carbon emissions by approximately 1%. However, storage will still increase emissions under the RTP when there is no carbon tax. Carbon taxes are vital to reduce the emissions of batteries. In particular, the high variance of MEFs can bring about significant emission reduction through arbitrage. For example, carbon taxes can reduce 4.9% of carbon emissions in ERCOT, whereas the emissions reduction in CAISO is only 3.0%. We also find that carbon taxes have diminished effects on emissions reduction as long as the carbon tax rate is sufficiently high to motivate arbitrage between high MEF and low MEF hours. When the carbon tax is sufficiently high, the ability to reduce emissions through storage technologies is mainly limited by the MEF difference across hours but can be enhanced by increasing the round-trip efficiency of the battery.

Table 1.4 presents the decomposition of storage-induced carbon emissions. The storage-induced carbon emissions reflect changes in emissions under a solar plus storage system compared to a stand-alone solar system. Emissions from energy losses measure the increase in emissions due to a round-trip efficiency of less than 100%. It is calculated by multiplying the energy loss during battery charge and discharge by the corresponding MEFs.[39] Emissions from energy arbitrage measure the difference between increased emissions from battery

39. DER-CAM assumes a battery with an RTE of 80% will face a 10% energy loss during charging and a 10% energy loss during discharging.

Table 1.3: Environmental Outcomes

	CAISO		ERCOT	
	CO_2 (kg)	Change (%)	CO_2 (kg)	Change (%)
Base	668,660	–	915,662	–
Solar Only	208,960	–	283,296	–
TOU - Solar + Storage	215,154	3.0	292,471	3.2
RTP - Solar + Storage	213,583	2.2	288,872	2.0
RTP CT - Solar + Storage	208,165	-0.4	274,097	-3.2
RTP HCT - Solar + Storage	202,730	-3.0	269,326	-4.9

Notes: (1) All percentage changes are relative to the solar-only case. (2) RTP, RTP CT, and RTP HCT stand for RTP with no, normal, and high carbon tax levels, respectively.

charge and avoided emissions from discharge. It is calculated by deducting the emissions from the energy loss from the total storage-induced carbon emissions.

As shown in Table 1.4, energy loss is the main cause of increased storage-induced emissions under TOU rates, as in Fisher and Apt (2017). The RTP can reduce emissions through energy arbitrage, but the RTP will also increase emissions from energy loss due to more frequent battery charges and discharges. Carbon taxes can substantially reduce carbon emissions from energy arbitrage and can often reduce emissions from energy loss as carbon taxes reduce the amount of charge and discharge in certain hours with high MEFs. Therefore, RTP plus carbon taxes can reduce storage-induced carbon emissions substantially, especially with a higher variance of MEFs.

It is worth noting that we assume a round-trip efficiency of 80%. If the round-trip efficiency reaches 90% (with more expensive battery technology), the emissions from energy losses could be reduced by 50%. In this case, RTP can reduce storage-induced carbon emissions more substantially.

Table 1.4: Decomposition of Storage-induced Carbon Emissions

	CAISO	ERCOT
	Storage-induced CO_2 (kg)	Storage-induced CO_2 (kg)
TOU - Solar + Storage	6,194	9,175
energy arbitrage	-144	396
energy loss	6,338	8,779
RTP - Solar + Storage	4,623	5,576
energy arbitrage	-8,089	-7,932
energy loss	12,712	13,508
RTP CT - Solar + Storage	-795	-9,199
energy arbitrage	-12,029	-18,021
energy loss	11,234	8,822
RTP HCT - Solar + Storage	-6,230	-13,970
energy arbitrage	-15,688	-23,059
energy loss	9,458	9,089

Notes: RTP, RTP CT, and RTP HCT stand for RTP with no, normal, and high carbon tax levels, respectively.

There are substantial seasonal effects on environmental outcomes under different retail tariffs. Figure 1.7 presents the emissions reduction of the RTP as compared to a TOU pricing for CAISO and ERCOT, respectively. In CAISO, the RTP reduces the most carbon emissions during the spring months but will increase emissions from July to January.[40] In contrast, in ERCOT, the RTP will reduce emissions in the summer months and increase emissions from December to April. Whether RTP will increase or decrease carbon emissions is determined by whether renewables could serve as the marginal technology. Specifically, it depends on both the renewable output and the system demand. RTP could reduce emissions in months where both the RTP rates and MEFs are low due to the high renewable output and low system demand.

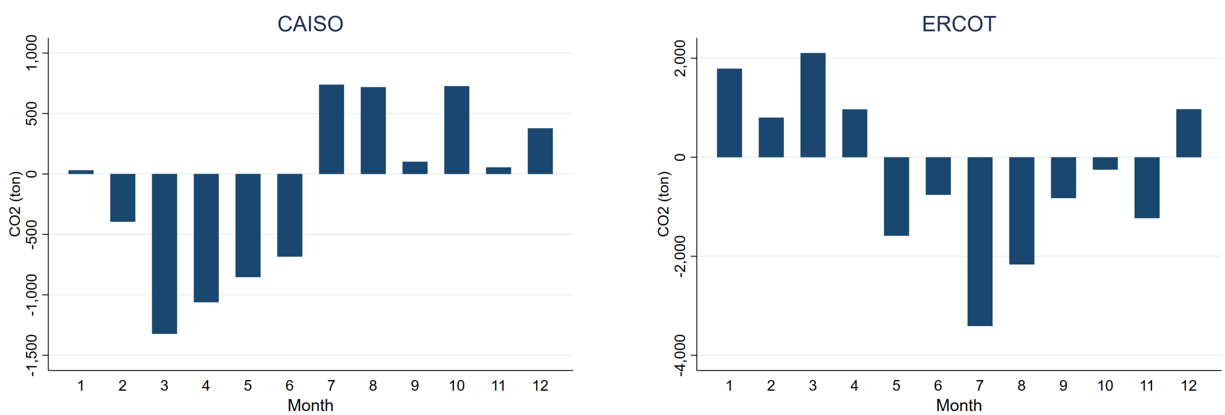


Figure 1.7: Carbon Reduction under the RTP by Month

The exogenous setting provides several key findings. First, with sufficient renewable penetration, RTP can reduce emissions compared to TOU rates through energy arbitrage. However, without carbon taxes, adding batteries to existing solar systems will still lead to increased carbon emissions under the RTP with a round-trip efficiency of 80%. This is because RTP increases the frequency of battery charge and discharge, increasing emissions as a result of energy losses. Increasing the round-trip efficiency of batteries can effectively reduce

40. Although solar output is the highest in July and August in CAISO, they appear less on the margin due to higher demand. Therefore, the emissions reduction from energy arbitrage is lower in these months.

emissions under RTP. RTP plus carbon taxes can reduce carbon emissions in most cases, given sufficient arbitrage opportunities.

Second, whether batteries can reduce carbon emissions in a solar plus storage system is determined by both the round-trip efficiency of the system and the variance of the MEFs. If the variance of MEFs is low, avoided emissions from energy arbitrage (given a price signal that shifts load from high to low emission intensity hours) might be insufficient to cover the energy loss. Therefore, a mandate that requires emissions reductions for batteries could affect the profitability of the storage system in most of the regions in the US where natural gas plants serve as the marginal plants for most hours.

Third, charging batteries with solar energy does not necessarily lead to emission reductions if solar energy can be used to replace a dirtier generation source on the margin. Whether it will reduce carbon emissions will be determined by a number of factors, including the RTE of the battery and what resources are on the margin in the evening when the sun sets and the battery is discharged.

There are several reasons why RTP and carbon taxes do not substantially reduce carbon emissions substantially compared to TOU in CAISO. First, the RTP and MEFs in our analysis are averaged over an hourly and monthly basis. In a real-time setting, the correlation between MEFs and RTP and the variance of MEFs can be more substantial, leading to more considerable emissions reductions through load shifting.[41] For example, on a very sunny day in May, the MEFs could be close to zero when solar panels generate electricity. Therefore, shifting the load from early evenings to solar generating hours will lead to much higher emissions reductions than solar export. Second, the MEFs are flat most of the months, reducing the potential for emissions reduction. Third, in the case of CAISO, the peak hours of TOU are highly correlated with high RTP periods, providing similar price signals.

41. Section 1.7.2 provides a robustness check for "real-time" RTP. Our results hold under both averaged and "real-time" RTP. However, due to data limitations, a robustness check for "real-time" MEFs is not available.

In addition, the RTP rates and MEFs are highly correlated, which increases the effects of a stand-alone RTP rate but reduces the effects of a carbon tax on charge and discharge decisions.

1.6.2 Endogenous Results

This section presents the results with endogenous solar and storage capacities that minimize total electricity and DER investment costs. We first look at the endogenous results for RTP in CAISO. Table 1.5(a) shows the optimized solar and storage investment decisions in CAISO for RTP at zero, normal, and high carbon tax levels, respectively. Under net metering, solar is compensated at the prevailing retail rate, which is less profitable under the RTP rate than the TOU rate. As a result, customers are much less likely to install solar under the RTP rate, causing higher carbon emissions. Under our investment and technological assumptions, solar panels will be profitable with a compensation rate of no less than 6 cents per kWh. Thus, solar panels will be installed only in the high carbon tax setting with an average RTP rate of 10 cents per kWh. Once the compensation rate is above the cut-off value calculated in Appendix A, consumers will install the maximum allowed capacity for solar PV, binding only by the roof space. Under RTP, storage investment is not profitable regardless of carbon tax levels. This means that the retail rate differences across hours are insufficient to support a profitable arbitrage. This finding contributes to the existing body of evidence indicating that storage remains economically unviable, especially when its role in preventing outages is not considered (Muehlenbachs and Brown 2023).

It is worth noting that these results are reached under a "smoothed" RTP based on three representative day types. Therefore, the arbitrage opportunities are less than in a case with a "real-time" RTP that varies by hour and day. Section 1.7.2 provides a discussion on how this could affect endogenous results.

Table 1.5: Endogenous Results for CAISO under Different Scenarios

Scenario	**Carbon Tax** ($/tonne)	**Solar Capacity** (kW)	**Storage Capacity** (kW)	**Costs** ($)	**CO_2 Emissions** (kg)
(a) RTP					
Solar	0	0	0	$192,212	668,660
Solar + Storage	0	0	0	$192,212	668,660
Solar	$51	0	0	$226,314	668,660
Solar + Storage	$51	0	0	$226,314	668,660
Solar	$152	599	0	$247,892	172,939
Solar + Storage	$152	599	0	$247,892	172,939
(b) TOU2					
Solar	0	599	0	$121,871	150,177
Solar + Storage	0	599	0	$121,871	150,177
Solar	$51	599	0	$131,093	150,177
Solar + Storage	$51	599	0	$131,093	150,177
Solar	$152	599	0	$149,356	150,177
Solar + Storage	$152	599	0	$149,356	150,177
(c) TOU5					
Solar	0	599	0	$147,302	150,177
Solar + Storage	0	599	2101	$134,398	169,036
Solar	$51	599	0	$161,135	150,177
Solar + Storage	$51	599	2115	$133,913	173,440
Solar	$152	599	0	$188,531	150,177
Solar + Storage	$152	599	2120	$132,891	173,484

Notes: (1) TOU2 and TOU5 are TOU pricing with peak-to-off-peak ratios of 2 and 5, respectively. (2) Costs are annual electricity costs that include both annualized investment costs for DER and annual electricity purchase costs. (3) CO_2 Emissions are annual CO_2 emissions based on customer consumption profile and DER operations.

Tables 1.5(b) and 1.5(c) show the optimized solar and storage investment decisions in

CAISO for TOU2 and TOU5, respectively. Under the TOU rate, customers have incentives to install solar and storage technologies to cover part or all of the electricity usage during the peak period. When solar generates most of its energy during the off-peak period, the investment decision for solar is mainly determined by the compensation rate during the off-peak period. In addition, whether batteries are installed could affect the size of the solar PV since battery charges increase the electricity demand during solar generation hours.[42] As shown in Table 1.5(b), under the TOU2 rate, consumers are willing to install solar PV because the off-peak rate can sufficiently cover the capital costs of solar. The optimal solar capacity is bound by the rooftop space. Due to a low peak-to-off-peak ratio, installing battery storage is not profitable under any carbon tax levels.

Table 1.5(c) shows the endogenous results under the TOU5 rate. Even with a lower off-peak compensation rate, installing solar PV is still profitable. Unlike the TOU2 case, installing battery storage is profitable due to higher peak-to-off-peak rate differences. In particular, the battery capacity is selected so that all peak period consumptions are covered. As a result, carbon emissions increased by approximately 15% as compared to the no storage (TOU2) cases.[43]

Table 1.6(a) shows the endogenous results for ERCOT under the RTP. Due to the lower compensation rate, consumers have incentives to install solar PV only if there is a carbon tax. Similarly to CAISO, storage is not profitable under all circumstances. These results suggest that relying on RTP to promote storage could be infeasible without government subsidies. The arbitrage opportunities under the RTP are not sufficient to cover its capital

42. Under the net-metering policy, the size of the solar PV can be limited by either the rooftop space or the total electricity consumption during the off-peak period. The latter constraint exists because once total solar generation exceeds total consumption, the compensation rate will drop to a level where additional solar capacity is not profitable. When batteries exist, total electricity consumption during the off-peak period will increase due to battery charging, thus increasing the optimal size of the solar PV, provided that the rooftop space constraint is not binding.

43. Without the rooftop space constraint, batteries do not necessarily increase emissions as they can induce larger solar PV capacities.

costs.

Table 1.6: Endogenous Results for ERCOT under Different Scenarios

Scenario	Carbon Tax ($/tonne)	Solar Capacity (kW)	Storage Capacity (kW)	Costs ($)	CO_2 Emissions (kg)
(a) RTP					
Solar	0	0	0	$114,780	915,662
Solar + Storage	0	0	0	$114,780	915,662
Solar	$51	599	0	$144,054	296,139
Solar + Storage	$51	599	0	$144,054	296,139
Solar	$152	599	0	$172,960	296,139
Solar + Storage	$152	599	0	$172,960	296,139
(b) TOU2					
Solar	0	599	0	$93,429	286,190
Solar + Storage	0	599	0	$93,429	286,190
Solar	$51	599	0	$104,169	286,190
Solar + Storage	$51	599	0	$104,169	286,190
Solar	$152	599	0	$172,960	286,190
Solar + Storage	$152	599	0	$172,960	286,190
(c) TOU5					
Solar	0	599	0	$77,166	286,190
Solar + Storage	0	599	0	$77,166	286,190
Solar	$51	599	0	$81,231	286,190
Solar + Storage	$51	599	0	$81,231	286,190
Solar	$152	599	0	$89,280	286,190
Solar + Storage	$152	599	2431	$58,695	375,985

Notes: (1) TOU2 and TOU5 are TOU pricing with peak-to-off-peak ratios of 2 and 5, respectively. (2) Costs are annual electricity costs that include both annualized investment costs for DER and annual electricity purchase costs. (3) CO_2 emissions are annual CO_2 emissions based on the customer consumption profile and DER operations.

Tables 1.6(b) and 1.6(c) present the optimized solar and storage investment decisions in ERCOT for TOU2 and TOU5, respectively. In ERCOT, solar can generate electricity during both off-peak and peak periods, leading to higher bill savings. Similarly to the CAISO case, installing solar PV is profitable under all retail tariff settings. In addition, as mentioned in Section 1.6.1, there exists a substitution effect between solar PV and batteries in ERCOT as solar generation can be used to offset peak period electricity purchase from the utility completely. As a result, installing batteries becomes unprofitable in most cases. An exception is the high carbon tax rate case under TOU5. This happens because even if solar exports are compensated at the wholesale rate, the profits from arbitrage can still cover the high capital costs of battery storage. As a result, emissions increased by about 30% compared to a non-battery case.

The endogenous case suggests that RTP alone cannot provide enough bill savings to justify the installation of solar and storage technologies at the prevailing costs. In this case, a high level of carbon taxes is needed to support the penetration of DER technologies under RTP. In addition, a high peak-to-off-peak ratio in TOU pricing does not necessarily lead to higher capacities of solar and storage and higher emissions reductions. Under our assumptions, the TOU2 rate generally performs better than RTP or TOU5 in terms of emission reduction.

1.7 Robustness Checks

1.7.1 Price Elasticity

In the default setting, we assume that electricity is perfectly inelastic. In reality, both the short- and long-term price elasticity of demand for electricity can differ from zero and have been extensively estimated in the literature (Andruszkiewicz et al. 2019). For example, (Burke and Abayasekara 2018) estimate the short-run price elasticities in the US from 2003 to 2015 and report an average elasticity of -0.11 for residential customers and -0.05 for commercial customers.[44]

As a robustness check, we relax the perfect inelastic assumption and assume a price elasticity of -0.1. For each retail tariff in our study, we derive the new demand profile by calculating the elasticity-adjusted demand in each hour.[45] For simplicity, we assume that the initial demand profile is simulated at a flat rate, which is derived from Equation (1.2). We use the new demand profiles to examine endogenous and exogenous cases for a supermarket in CAISO.

Table 1.7 presents the adjusted environmental outcomes for the exogenous case. Compared to the benchmark case (Table 1.3), the TOU rates generate lower emissions as they lead to less electricity consumption during the peak period, which is highly correlated with high emissions intensity hours. In contrast, RTP rates lead to much higher emissions as consumers consume more electricity in both peak and off-peak periods due to lower volumetric charges in both periods.[46] As in the benchmark case, carbon taxes can further reduce emissions by aligning price signals with emissions. Carbon taxes will also raise the energy rate level and lead to lower carbon emissions because customers will consume less electricity. As shown in Table 1.7, elasticity has minimal effect on storage-induced carbon emissions. This is because a change in electricity demand will have a minimal impact on the charge and discharge decisions of the battery.

Table 1.8 shows the elasticity-adjusted endogenous results for CAISO under RTP. As shown in Table 1.8(a), with elasticity, customers under RTP tend to consume more energy,

44. The short-run price elasticities for commercial and residential customers estimated by the EIA is -0.08 and -0.13, respectively (EIA 2021b).

45. The elasticity-adjusted demand D_e equals $D + \Delta D$, where D is the original demand, and $\Delta D = -0.1(R/\Delta R)D$. We assume that the initial demand profile is simulated under a flat rate R, which can be calculated by equating $rate_{peak}$ and $rate_{off}$ with R in equation (2) from section 5.5.2. ΔR is the difference in electricity rate between R and the rate from our retail rate design.

46. Borenstein and Bushnell (2022) suggest that the electricity prices in California are too high compared to the social marginal costs of electricity.

Table 1.7: Elasticity-Adjusted Environmental Outcomes for CAISO

Scenario	CO_2 Emissions (kg)	Change
TOU2 - Solar Only	208 251	
TOU2 - Solar + Storage	214 531	3.0%
TOU5 - Solar Only	202 123	
TOU5 - Solar + Storage	207 887	2.9%
RTP - Solar Only	254 294	
RTP - Solar + Storage	259 115	1.9%
RTP CT - Solar Only	241 324	
RTP CT - Solar + Storage	243 608	0.9%
RTP HCT - Solar Only	215 638	
RTP HCT - Solar + Storage	217 573	0.9%

Notes: (1) All changes are relative to the solar-only case of the same retail rate design. (2) RTP, RTP CT, and RTP HCT stand for RTP with no, normal, and high carbon tax levels, respectively.

resulting in higher emissions. As a result, emissions will increase by 6.7%, 4.8%, and 0.5% under the zero, normal, and high carbon taxes, respectively. This suggests that a very high carbon tax is needed to reduce the energy consumption increase brought about by the lower RTP rates.[47]

47. It is worth noting that the current retail rate in CAISO is higher than marginal costs, rendering it inefficient. Lower RTP rates could potentially increase emissions, but could generally improve the overall efficiency of electricity consumption (Borenstein and Bushnell 2022).

Table 1.8: Elasticity-Adjusted Endogenous Results for CAISO

Scenario	Carbon Tax ($/tonne)	Solar Capacity (kW)	Storage Capacity (kW)	Costs ($)	CO_2 Emissions (kg)
(a) RTP					
Solar	0	0	0	$195,616	713,994
Solar + Storage	0	0	0	$195,616	713,994
Solar	$51	0	0	$230,270	701,024
Solar + Storage	$51	0	0	$230,270	701,024
Solar	$152	599	0	$269,613	381,140
Solar + Storage	$152	599	0	$269,613	381,140
(b) TOU2					
Solar	0	599	0	$150,901	145,799
Solar + Storage	0	599	0	$150,901	145,799
Solar	$51	599	0	$166,619	145,799
Solar + Storage	$51	599	0	$166,619	145,799
Solar	$152	599	0	$193,824	145,799
Solar + Storage	$152	599	0	$193,824	145,799
(c) TOU5					
Solar	0	599	0	$151,310	145,799
Solar + Storage	0	599	1139	$134,714	159,230
Solar	$51	599	0	$164,063	145,799
Solar + Storage	$51	599	1098	$137,641	166,198
Solar	$152	599	0	$184,160	292,604
Solar + Storage	$152	599	1065	$141,897	164,458

Notes: (1) TOU2 and TOU5 are TOU pricing with peak-to-off-peak ratios of 2 and 5, respectively. (2) Costs are annual electricity costs that include both annualized investment costs for DER and annual electricity purchase costs. (3) CO_2 emissions are annual CO_2 emissions based on elasticity-adjusted customer consumption profiles and DER operations.

Tables 1.8(b) and 1.8(c) show similar results. Compared to the benchmark case, elasticity can affect environmental outcomes through two channels. First, when customers react to the energy rates, they consume less during the peak period. Therefore, emissions will decrease when the peak period coincides with high emission-intensity hours. Second, since storage is used to target peak periods under the TOU, consumers are less motivated to install storage when they consume less during the peak period. Because storage tends to increase emissions under the TOU rates, emissions under the TOU rates will be reduced with a more negative elasticity.

Overall, when consumers react to energy rates, they will consume more energy under RTP, leading to higher emissions. Under TOU, consumers will consume less energy during the peak period and will install batteries with smaller sizes, leading to lower emission levels.

Our calculations are done without the influence of solar or battery technologies on consumer behaviors. Consumers may change or shift their electricity demand in response to these technologies. For example, a consumer may consume more energy during solar generation hours to avoid net surplus exports or consume more energy in general since energy becomes cheaper, known as the rebound effect (Beppler et al. 2023). Our analysis does not consider these effects, but considering the relatively low elasticity of demand for commercial customers, we anticipate that the results will be similar to our analysis in Section 1.7.1.

1.7.2 "Real-time" RTP

As DER-CAM only allows representative RTP to be averaged over a month-hour basis, our primary analysis tends to underestimate the arbitrage opportunities (e.g. from price spikes) brought about by the RTP. This section uses a "real-time" RTP that varies hourly to examine how our baseline results might deviate from the real-world outcomes. As in the benchmark case, we assume that the battery is operating under perfect foresight: the customer has perfect information about the demand and RTP in the future. Unlike the benchmark case where the RTP is averaged over three representative days (week, weekend, peak), this section uses the “real-time” RTP, holding other factors constant.

To carry out the analysis, we develop an algorithm following the same objective function and constraints described in Section 1.5.1. In particular, we develop a mixed-integer linear programming model to simulate the charge and discharge decisions of a battery using consecutive hourly inputs. While our algorithm performs the same as DER-CAM for exogenous cases, we rely on DER-CAM to study the endogenous cases. We use LMPs in April 2019 in CAISO to construct two sets of RTP: a representative RTP averaged hourly over the three representative days and a “real-time” hourly RTP that varies by hour and day. We use April 2019 in CAISO because April has a significant variance of LMPs, and the arbitrage opportunities could be significantly underestimated in the benchmark case. The summary statistics for the two sets of RTP are shown in Table 1.9. The standard deviation of the real-time RTP is slightly higher than in the benchmark case, but not by a significant margin.

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
RTP - benchmark	0.037	0.017	0.011	0.124
RTP - "real-time"	0.037	0.021	-0.004	0.124

Table 1.9: Summary Statistics of the RTP

The environmental results are shown in Table 1.10. Surprisingly, the difference between the benchmark and the “real-time” cases is minimal. This reflects that the RTP averaged over three representative days can reasonably represent “real-time” pricing well. This could be due to two reasons. First, in the day-ahead market, the variance of LMPs is slight, and the LMP patterns are relatively robust across days. In other words, a price spike is very unlikely to happen in the day-ahead market. Second, arbitrage opportunities during days with subnormal levels of LMPs are well captured by the “peak” representative day.

	Total Carbon (kg)	Total Bill ($)
Solar-only	17,173	2,453
RTP - benchmark	17,098	2,070
RTP - "real-time"	17,053	2,043
RTP CT - benchmark	16,280	2,905
RTP CT - "real-time"	16,233	2,940

Table 1.10: Environmental Outcomes Comparison

1.8 Conclusion

Our paper investigates whether RTP and a carbon tax could be used to cut storage-induced carbon emissions compared to the more traditional TOU rates. We find that with better timing of charging and discharging, RTP can reduce carbon emissions compared to a TOU rate. However, emission reductions are often insignificant when TOU rates are carefully designed with batteries that have an 80% RTE. In general, RTP alone cannot eliminate the emissions resulting from the use of batteries. This is because the increase in emissions from energy loss largely offsets the reduction in emissions from energy arbitrage. However, when the battery RTE increases to 90%, RTP has the potential to eliminate storage-induced emissions through energy arbitrage even without a carbon tax. When the battery RTE is at 80%, a carbon tax is essential for the elimination of storage-induced carbon emissions.

The effectiveness of RTP plus carbon taxes in reducing emissions through energy arbitrage is determined by the variance of the MEFs. In most regions where renewable penetration is low and natural gas plants generally serve in the margin, RTP is likely to not incur emission reductions. RTP and carbon tax can reduce the most substantial emissions when the region has both renewable energy resources and coal-fired power plants. In this circumstance, removing the net-metering compensation policy would only slightly increase carbon emissions.

Taking investment decisions into consideration, we find that RTP is generally insufficient to promote the adoption of solar plus storage technologies. Only with a very high carbon tax level will consumers be willing to install solar and batteries under the RTP. As a result, TOU rates often provide better environmental results than RTP. Under RTP, solar and battery costs must be reduced by 20% and 50%, respectively, to incentivize consumers to adopt them.

These findings provide important policy insights for retail rate reforms. Our analysis highlights the importance of using RTP and carbon taxes to provide real-time price signals to reduce carbon emissions from batteries. In addition, we show that government subsidies will be required to promote the adoption of DER technologies if RTP is implemented. This implies that it is not cost effective to subsidize batteries at the current cost level from an environmental point of view, considering the relatively low social gains from the reduction of emissions.[48]

There are three main limitations to our analysis that require future research. First, the RTP and MEFs used in our analysis are averaged on an hourly basis on three typical days. As a result, the effects of RTP on the charge and discharge decisions could be underestimated.[49]

Second, we only employ two simple retail rate structures, RTP and TOU rates. Other commonly used rate structures (such as demand charges and tiered charges) are left for future studies.

48. It is worth noting that battery storage systems can provide indirect environmental benefits by enhancing grid reliability, particularly in managing the intermittency of renewable energy sources. However, this is beyond the scope of our study.

49. The robustness check from section 1.7.2 is conducted to deal with the issue, but the MEFs are still not real-time.

Third, our paper is static and only considers the current level of renewable penetration. As more adoptions of solar and storage occur, RTP could be lower, and MEFs tend to be flatter. As a result, the incentives for adopting solar plus storage systems could drop significantly.

Fourth, our paper focuses exclusively on investment decisions driven by energy arbitrage opportunities arising from time-varying retail tariff designs. In reality, customers may choose to install batteries for various reasons. In particular, customers might install batteries to avoid maximum demand charges and prevent outages (Boampong and Brown 2020; Muehlenbachs and Brown 2023). These different incentives should be explored further in future research.

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1.9 Appendices

Appendix A: Investment Decisions

The investment decisions can be illustrated by the following example. Suppose a consumer chooses the optimal size of a solar plus storage system that minimizes the bill payments. The customer faces a time-of-use pricing of two periods, whereas the rates he pays in period 1 and period 2 is p_1 and p_2, respectively. For simplicity, we assume that the solar panel only generates electricity in period 1.

The electricity demanded by the customer in each period is d_1 and d_2 per day. The utility company has a net-metering policy for solar energy. If the solar output is lower than d_1, the customer is compensated at the retail rate, p_1. If solar output exceeds d_1, the excess power will be compensated for at the net surplus compensation rate e where $e < p_1$.

The variable cost of solar and battery is VC_p and VC_s per kW. The initial investment costs are financed by the customer with a discount rate of i. The payback period is equal to the lifetime of the solar panel (t_p) and the batteries (t_s). Therefore, the marginal cost of solar (C_p) and battery (C_s) per kW per day can be calculated as:

$$C_{p,s} = VC_{p,s} \cdot \frac{i}{365(1 - \frac{1}{(1+i)^{t_{p,s}}})}$$

Suppose the capacity of solar and battery is K_p and K_s, respectively. The daily solar output can be described as σK_p, where σ is the average peak-sun hours. When there is no battery technology, the daily marginal benefits of solar energy equal $p_1\sigma$ if $K_p \leq d_1/\sigma$, or $e\sigma$ if $K_p > d_1/\sigma$. As a result, the customer will install a solar panel with capacity d_1/σ as long as $p_1 \geq \frac{C_p}{\sigma} > e$.[50] Similarly, a customer will install a solar panel up to the physical constraint if $e \geq \frac{C_p}{\sigma}$.

50. The rate p_1 should be no smaller than 4.8 cents under the following assumptions. The variable cost of solar is $1,750. The average peak-sun hours is 4. The discount rate is 3%. The maximum lifetime of a solar panel is 25 years. This cut-off value is much smaller than the usual retail rate, indicates strong motivations for installing solar under the TOU rates.

Suppose that a battery has a round-trip efficiency of r. If $p_2 > p_1$, the customer can store a unit of energy at p_1 and sell it at rp_2, and vice versa. The daily marginal benefits of storage can be given as $rp_2 - p_1$if $K_s \leq d_2/\Delta\theta$ where $\Delta\theta$ is the difference between the max and min battery charge status. If the TOU rate only applies on weekdays (260 out of 365 days), the customer will install a battery with a capacity of $d_2/\Delta\theta$ if $rp_2 - p_1 \geq \frac{365}{260}C_s$. Moreover, as storage increases the electricity demanded in period 1, it could also increase the solar capacity by d_1/σ. Thus, the total marginal benefit is the sum of the two effects.

Our simple model can be modified to include situations where solar can generate during both peak and off-peak period, and when there is no net-metering policy. For example, suppose that solar can generate electricity during both peak and off-peak period, and the solar output during peak and off-peak period is $\sigma_1 K_p$ and $\sigma_2 K_p$, respectively. The marginal benefits of solar is the output weighted compensation rate. For example, when $\sigma_i K_p < d_i$ for $\forall i = 1, 2$, the marginal benefit is given by $\sigma_1 p_1 + \sigma_2 p_2$. Suppose $\sigma_1 > \sigma_2$ and $d_1 < d_2$, the marginal benefits will drop to $\sigma_1 e_1 + \sigma_2 p_2$ when $\sigma_1 K_p \geq d_1$and $\sigma_2 K_p < d_1$. If $\sigma_2 K_p \geq d_1$, the marginal benefits will drop further to $\sigma_1 e_1 + \sigma_2 e_2$. The investment decision for solar (whether solar generation should cover the peak-period electricity consumption, off-peak-period consumption, or both) is therefore determined by whether the output weighted compensation rates exceed the cut-off value.

The above example can be further modified to analyze a case where there is no net-metering. Suppose the hourly electricity consumption d_{mh}, energy rate p_{mh}, and hourly peak-sun hours σ_{mh} varies with month $m = 1, 2, ..., 12$ and hour $h = 1, 2, ..., 24$. Once solar generation exceeds the electricity consumption in a hour, the net surplus solar exports are compensated at a lower rate e_{mh}. Suppose $K_{mh} = \frac{dmh}{\sigma_{mh}}$ is the minimum solar capacity needed to completely offset electricity consumption in month m and hour h. We can rank K_{mh} by size and denote them as K_1, K_2,...,K_n, ..., K_N where K_1<K_2<...<K_N. The marginal benefits is thus $B_n = \sum_{i=1}^{n} \sigma_i e_i + \sum_{i=n+1}^{N} \sigma_i p_i$ when $K_p = K_n$. The capacity is chosen at K_{n^*} so that

$B_{n^*} > 365 \cdot C_p > B_{n^*+1}$.

Appendix B: DER-CAM Algorithm

This section outlines the objective function and key constraints for the optimization algorithm in our endogenous setting following Boampong and Brown (2020). In our analysis, the algorithm is used to minimize total costs:

$$
\begin{aligned}
C = & \sum_m Fixed + \sum_m \sum_d \sum_h Demand_{m,d,h} \cdot Rate_{m,d,h} \\
& + \sum_j [(VCC_j \cdot CAP_j) \cdot An_j + CAP_j \cdot OMP_j] \\
& - \sum_m \sum_d \sum_h Export_{m,d,h} \cdot Compensation_{m,d,h}
\end{aligned}
$$

Notation	Variable
$Fixed$	Monthly Fixed Charge
$Demand_{m,d,h}$	Hourly Electricity Demand at Hour h, Day d, and Month m
$Rate_{m,d,h}$	Hourly Electricity Rate at Hour h, Day d, and Month m
VCC_j	Variable Capital Cost of Technology j
CAP_j	Capacity of Technology j
An_j	Annuity Factor
OMP_j	Operational Cost of Technology j
$Export_{m,d,h}$	Solar Exports at Hour h, Day d, and Month m
$Compensation_{m,d,h}$	Solar Compensation Rate at Hour h, Day d, and Month m

Table 1.11: Notation Description

subject to the following constraints:

1. Supply equals demand at any time.

2. Solar output at each hour is determined by the solar radiation in the corresponding hour, solar panel efficiency, and capcity of solar system.

3. Battery charge and discharge constraints:

(a) the current battery charge status equals the net charge plus the charge status from last period minus enregy losses.

(b) the current battery charge must be higher than the minimum charge status and lower than the maximum charge status required by the battery.

(c) hourly charge and discharge rate is limited by the charge and discharge rate.

Appendix C: Demand Profiles

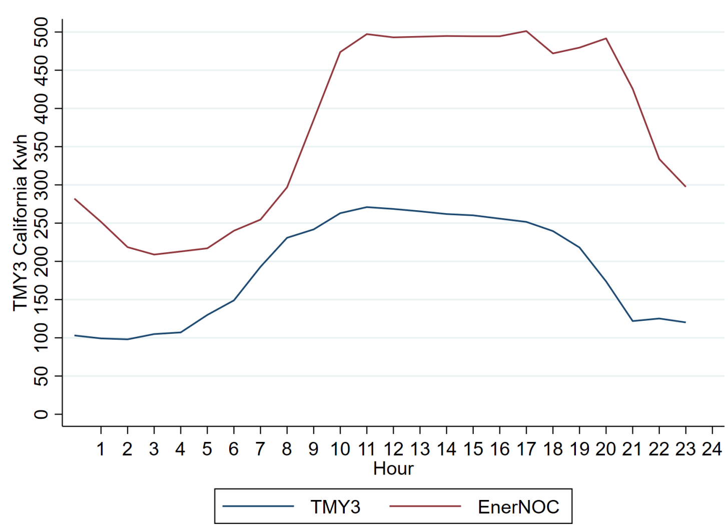

Figure 1.8: Demand Profile for Supermarkets

Appendix D: Retail Tariff Designs

Load Profile	CAISO	ERCOT
Energy Rate	0.114	0.063
TOU2 - Peak	0.188	0.103
TOU2 - Off-peak	0.094	0.051
TOU5 - Peak	0.307	0.163
TOU5 - Off-Peak	0.061	0.033
TOU2 CT - Peak	0.222	0.145
TOU2 CT - Off-peak	0.111	0.072
TOU5 CT - Peak	0.363	0.230
TOU5 CT - Off-Peak	0.073	0.046
TOU2 CTH - Peak	0.290	0.228
TOU2 CTH - Off-peak	0.145	0.114
TOU5 CTH - Peak	0.473	0.362
TOU5 CTH - Off-Peak	0.095	0.072
Avg RTP Rate	0.039	0.039
Avg CT - RTP Rate	0.060	0.065
Avg CTH - RTP Rate	0.101	0.117

Table 1.12: Retail Tariff Designs

Appendix E: Average Month-hour RTP

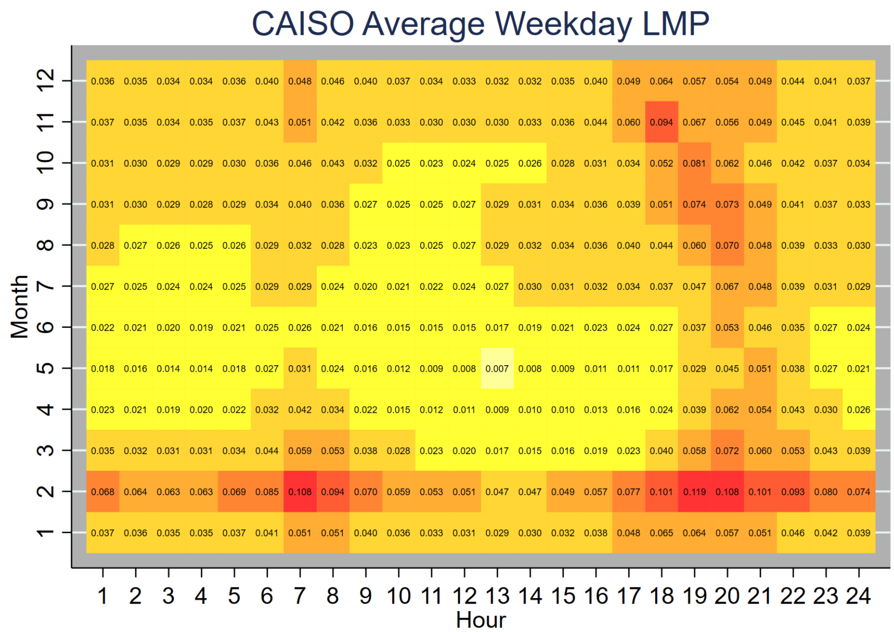

Figure 1.9: CAISO Average Weekday LMPs ($/kWh)

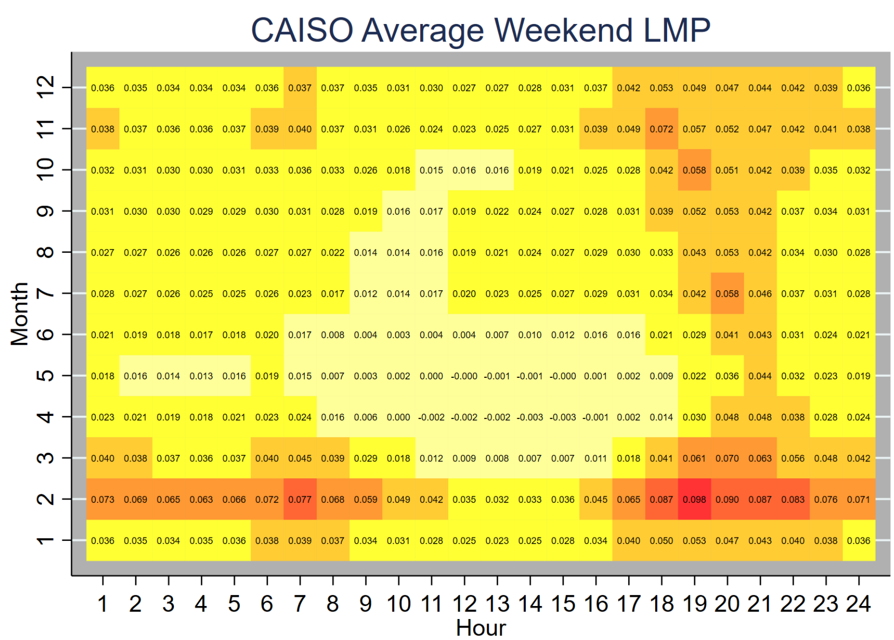

Figure 1.10: CAISO Average Weekend LMPs ($/kWh)

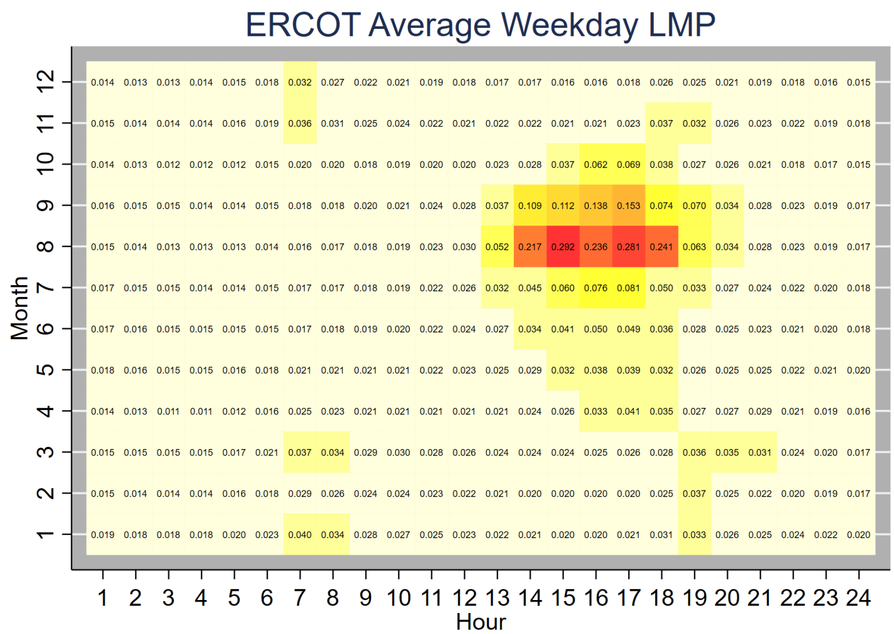

Figure 1.11: ERCOT Average Weekday LMPs ($/kWh)

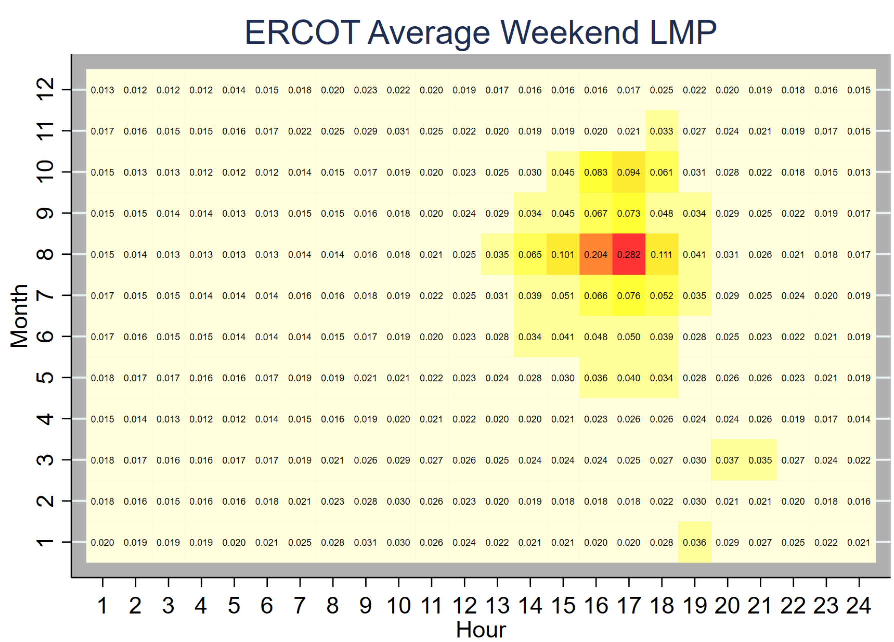

Figure 1.12: ERCOT Average Weekend LMPs ($/kWh)

Chapter 2

Estimating Locational Marginal Emissions Considering Transmission Congestion

2.1 Introduction

Electricity generation is one of the most carbon-intensive sectors in the US, accounting for 25% of all carbon emissions (EPA 2024). Transitioning to renewable generation resources such as wind and solar is critical to decarbonizing the energy sector. Because renewable energy resources are often located in remote regions, substantial investments in transmission capacity are needed to deliver energy from renewable-rich remote regions to population centers. However, the expansion of transmission capacity is often too slow to catch up with the rapid expansion of renewable generation, causing severe transmission congestion in certain regions (Joskow 2020).[1]

In a restructured electricity market, generators are called upon to supply electricity based on ascending order of price offers to minimize the costs of supplying electricity through a

1. For example, in Texas, where wind penetration is high, the electric system had at least one congested transmission line for 75% of hours in 2022, resulting in a total congestion loss of over 5 billion dollars (Potomac Economics 2023b). In California, which is rich in solar energy, transmission congestion occurred 50% of hours, resulting in a congestion loss of over 1.7 billion US dollars (CAISO 2023a).

procurement auction system. The generator with the lowest price offers will be called upon first, followed by the next lowest-priced generator, until the electricity supply meets demand. Transmission congestion can affect this sequence of supply (also known as the “merit order”) as energy generated in congested areas cannot be used to meet supply in uncongested areas, and vice versa. For example, when a population center (powered by coal and natural gas) cannot receive wind energy generated in a remote region due to transmission congestion, a nearby fossil fuel generator must be called upon to meet local electricity demand. Consequently, transmission congestion can have a locational impact on emissions. In particular, it can affect the locational marginal emissions factors (MEFs), which measure the change in locational emissions for an incremental change in local demand. MEFs are a critical parameter in the evaluation of policies and technologies that can shift energy loads, such as distributed energy resources (DER) or electric vehicles.[2]

In addition, large load centers, such as bitcoin mining operations and data centers, have increasingly impacted the electricity grid. In particular, where to locate these load centers has become a topic of considerable debate (Rhodes et al. 2021; Stoll et al. 2023). For instance, it has been argued that placing load centers in regions with high renewable penetration can significantly reduce carbon emissions and increase the economic value of renewable energy resources (Stoll et al. 2023). Understanding locational MEFs is crucial for assessing the environmental impact of these load centers.

To illustrate how transmission congestion affects MEFs, consider two regions: a remote region powered by wind energy and a densely populated region powered by coal and natural gas. When there is no transmission constraint between the two regions, generators will be dispatched based on the merit order, and the two regions will share the same MEFs because the same generator can respond to a demand increase in either region. However, when

2. DER technologies are customer-sited technologies that can generate and store energy on or near the site of an end user (Brown and Sappington 2017a). In this paper, DER technologies refer to rooftop solar panels and behind-the-meter (BTM) batteries.

congestion occurs, the merit order will split into two parts as local demand can only be met by local generators, leading to different MEFs. For example, in the absence of congestion, when the supply of wind energy in the remote region exceeds local demand, the excess energy will be delivered to the populated region. When there is a constraint to the outflow of wind energy, the extra wind energy will be curtailed. In this case, a unit increase in local electricity demand in the remote region will not increase emissions, resulting in zero marginal emissions in this region. In the meantime, local fossil fuel generators will be needed to meet the demand increase in the populated region, resulting in positive MEFs.

Different locational MEFs caused by transmission congestion will lead to different locational environmental values of DERs, measured by the potential mitigation of carbon emissions. DER technologies can reduce or shift load in certain hours and impact emissions based on the MEFs of the corresponding hours. For example, a battery can reduce electricity demand during discharging and increase electricity demand during charging. Based on the load shifts and MEFs during charging and discharging, the environmental value of a battery can be calculated as the net emissions reduction (avoided emissions minus created emissions), which will vary by location, given different locational MEFs.

Similarly, the environmental impacts of a load center may differ significantly depending on its location and the corresponding locational MEFs. By strategically placing load centers in regions with lower MEFs, carbon emissions can be minimized.

For simplicity and given data limitations, MEFs are measured with the assumption that all generators are used to meet local demand, regardless of local transmission conditions (e.g., Siler-Evans et al. 2012; Graff Zivin et al. 2014; Sexton et al. 2018; Holland et al. 2022). As a result, MEFs are often measured in broad regions with minimal energy imports and exports across regions (e.g., Siler-Evans et al. 2012; Graff Zivin et al. 2014) or in small subregions, assuming that local demand is met entirely with local generation (e.g., Sexton et al. 2018;

Holland et al. 2022). In the first case, MEFs can only provide an average measure across multiple subregions and overlooks locational differences. In the second case, the MEFs do not capture generation resources located outside of the subregion. As transmission congestion can greatly affect the marginal emissions in a particular subregion, locational MEFs that take transmission conditions into consideration are needed to capture the locational environmental values of DER technologies or to evaluate other energy-shifting technologies and policies.

Our paper proposes a novel estimation method to estimate locational MEFs while considering transmission congestion. We use an endogenous regime-switching model to estimate the MEFs in congested and uncongested regimes. Then, we use the congestion-weighted MEFs to calculate the environmental values of DER technologies located in remote regions with high wind penetration versus more population-dense regions powered primarily by natural gas and coal. Our paper has two primary objectives. First, we aim to understand how transmission congestion could affect locational MEFs in different regions, especially with different levels of renewable penetration. Second, we aim to understand how locational environmental values of DERs could be impacted by transmission congestion, highlighting the importance of using locational MEFs to make policy decisions.

Our paper focuses on the territory of the Electric Reliability Council of Texas (ERCOT). This territory is particularly interesting because more than 80% of wind energy resources are located in one remote subregion (the West load zone) of ERCOT (Fell et al. 2021). Transmission congestion has become a major barrier to renewable integration in ERCOT (Deniel and Gomberg 2021). In 2020, 5% of all wind generation in ERCOT had to be curtailed due to insufficient network capacity, one the highest among regional transmission organizations (Deniel and Gomberg 2021).

We find that the traditional estimation method can greatly overestimate or underestimate the locational MEFs in regions with high wind penetration. In particular, when congestion is present, the average MEFs in the West load zone are 20% less than the ERCOT-wide MEFs estimate. In addition, the MEFs estimated using our method are 30% higher than the alternative MEFs estimation that assumes that the West zone is fully "independent". Applying our estimation to the DER technologies, we find that transmission congestion can greatly reduce the environmental values of solar in remote windy areas. However, congestion tends to increase the variance of the MEFs and may increase the environmental values of energy storage systems. For example, when the system is congested due to excessive wind energy, a storage system located in the remote region can store clean power that would otherwise be curtailed and discharge the stored power when the system is uncongested.

This paper sheds light on the ongoing rate design discussion regarding the incorporation of environmental attributes in the compensation of DERs, especially rooftop solar panels. The environmental value is a crucial component in the economic value of a DER and should be included in the "value of DER" tariffs where the DER compensation aligns with the underlying economic value of a DER (Minnesota Department of Commerce 2014).[3] However, the environmental value is generally set at a predetermined rate, leading to a suboptimal level of DER compensation. Our paper highlights the importance of incorporating transmission congestion when considering the locational environmental values of DER.[4]

Our paper contributes to three strands of literature. The first relates to a large literature that relies on MEFs to evaluate policy and technology interventions, particularly energy storage and EVs (e.g., Graff Zivin et al. 2014; Siler-Evans et al. 2012; Holland et al. 2016). Previous studies that estimate MEFs have focused on coal and natural gas generators only, assuming non-emitting sources, such as wind, solar, and hydro, rarely contribute to marginal generation (Li et al. 2017). However, due to transmission constraints and improved dispatch-

3. See Section 2.2.2 for a detailed discussion.

4. Section 2.2.2 provides a detailed discussion on the ongoing rate design discussion regarding DER environmental values and compensations.

ability for renewables, renewables could affect MEFs substantially.[5] In addition, MEFs from previous studies do not consider local constraints, and therefore overlook regional differences. To the best of our knowledge, our paper is the first to investigate how congestion affects MEFs in regions with different energy sources. This provides valuable insights for evaluating locational environmental values for DER technologies and EVs.

Second, our paper contributes to the literature that looks at the locational environmental values of DERs based on locational MEFs. Our paper is related to work by Callaway et al. (2018) and Sexton et al. (2018), who focus on the locational environmental values of rooftop solar across the US based on locational MEFs, and Fisher and Apt (2017), who use MEFs in different jurisdictions to estimate the environmental value of battery storage technologies. Our paper differs from theirs by considering the impact of transmission congestion. In contrast, they assume that locational MEFs are only affected by local generators.

Third, our paper contributes to the literature that identifies congestion as a barrier to renewable integration (e.g., Fell et al. 2021). In particular, our research sheds light on how transmission congestion will affect the environmental values of rooftop solar and batteries. Several papers have documented that transmission congestion will reduce the environmental values of renewables (e.g., Hitaj 2015; Fell et al. 2021). Our paper differs from theirs by first estimating the locational MEFs. This allows us to easily compare environmental outcomes with different counterfactual settings.

The paper proceeds as follows. Section 2.2 provides the conceptual framework of our paper. Section 2.3 provides the background information on Texas's electricity market. Section 2.4 details the data used in our analysis. Section 2.5 presents the methodology for estimating the MEFs. Section 2.6 presents the main results. Section 2.7 discusses the environmental values of DER. Section 2.8 concludes.

5. For example, neglecting the effects of renewables can lead to a 30% overestimation of MEFs in the Midcontinent Independent System Operator (MISO) System in the US (Li et al. 2017).

2.2 Conceptual Framework

This section illustrates how transmission congestion could affect the locational environmental values of DER technologies using a simple numerical example.

2.2.1 Congestion and Locational MEFs

Consider two regions: a remote region (West) powered by wind farms and natural gas power generators and a population-dense region (East) powered by natural gas and coal-fired generators. The two regions are connected through a transmission line, which will be congested whenever the power flow (Q) between the two regions exceeds the transmission capacity, K. Electricity demand in each region is represented by D_i where $i = \{West, East\}$.

Figure 2.1 summarizes the assumed generation capacity, marginal cost, and marginal emissions rate for the power plants in each region. The wind farms in the West can provide 1,000 MWh of wind energy at zero marginal costs and zero emissions. The natural gas power plants in the West can provide another 1,000 MWh of electricity, with a marginal cost of \$50 per MWh and a marginal emissions rate of 0.5 tonnes per MWh. In the East, the coal-fired power plants can provide 2,500 MWh of electricity, with a marginal cost of \$20 per MWh and a marginal emissions rate of 1 tonne per MWh. The natural gas plants can provide another 1,500 MWh of power in the East, with a marginal cost of \$40 per MWh and a marginal emissions rate of 0.5 tonnes per MWh. We assume the maximum transmission capacity between the two regions is 500 MWh. The generators will be dispatched based on their marginal costs. Further, we assume that the demand for energy in the East and West regions falls within the intervals of $D_E \in [2,000, 4,000]$ and $D_W \in [0, 2,000]$, respectively.

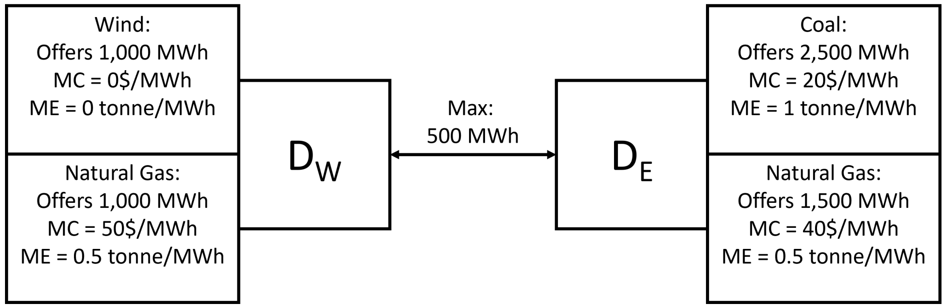

Figure 2.1: Numerical Example Setting

In this simple example, we will show that the electricity demand in the West will determine whether the system is congested. Further, when the system is uncongested, the marginal emissions rates are the same across regions and will be determined by the marginal power plant[6] in the East. When the system is congested, the marginal emissions rate in the West will be equal to or lower than that in the East, depending on the electricity demand in both regions.

Figure 2.2 presents the locational price and marginal emissions under different combinations of loads in the East and West. If $D_W < 500$, power will flow from the West to meet demand in the East via generation from the wind plant. The system will be congested (outflow congestion in the West) because the transmission capacity is lower than $Q = 1000 - D_W$, and the extra power $(500 - D_W)$ from wind will be curtailed. In this case, a marginal increase in the West load will not increase emissions but reduce wind curtailment. As a result, the MEF in the West will be zero. In the East, the marginal emissions rate will be either 1 tonnes/MWh (if $D_E \in [2000, 3000)$) or 0.5 tonnes/MWh (if $D_E \in [3000, 4000]$) depending on the marginal generation technology. It is worth noting that during congestion in the current example, a slight expansion of the transmission capacity will not change the marginal emissions rate in either region.

6. The marginal power plant is the power generator used to meet the last MWh of electricity demand.

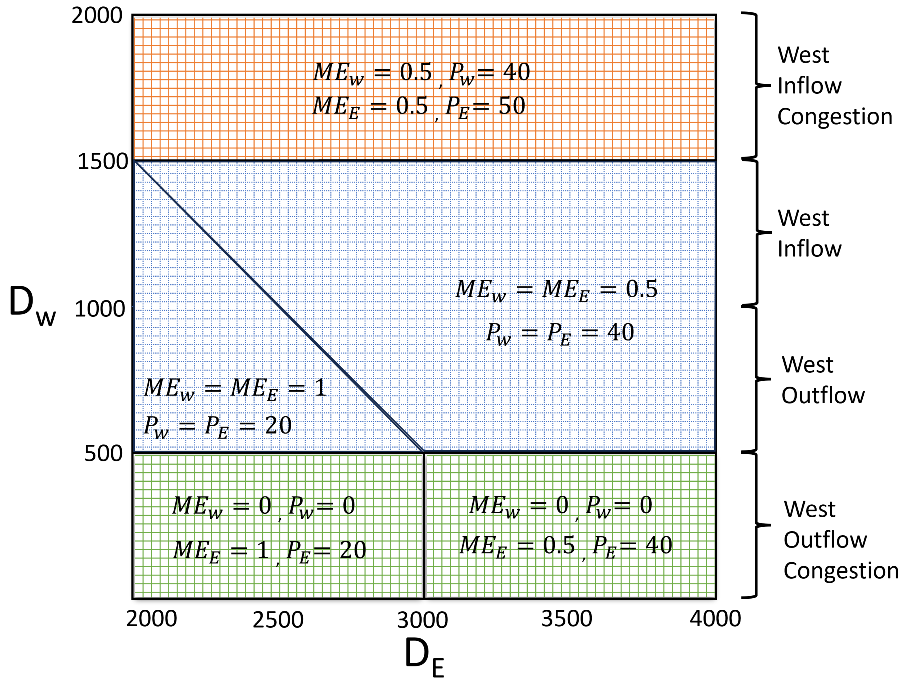

Figure 2.2: Numerical Example Illustration

If $500 \leq D_W \leq 1,000$, the wind power will flow from the West to the East without congestion. The marginal emissions rate will be the same across regions. Similarly, if $1000 < D_W \leq 1,500$, power will flow from the East to the West without congestion, leading to the same MEFs across regions. For both cases, the system MEF is determined by the system load $(D_W + D_E)$. As shown in Figure 2.2, the marginal emissions rate is determined by the marginal generation technology in the East. If $D_W + D_E \leq 3,500$, coal-fired plants will be the marginal plants whereas natural gas plants will be the marginal plants if $D_W + D_E > 3,500$.

Finally, when $D_W > 1,500$, the power will be restricted from the East to the West, causing inflow congestion to the West. For example, when the West load is 1,800 MWh, the marginal emissions rate in the West will be determined by its natural gas units. In our simple example, natural gas power plants in both regions have a marginal emissions rate of 0.5 tonnes/MWh. When the marginal fuel in the East is natural gas, the marginal emissions rate across the regions will be the same. However, if we relax the assumption for D_E and let $D_E < 2000$, coal will be used as the marginal fuel in the East. In this case, an inflow congestion in the West will still lead to lower West MEFs than the East.

Our simple example indicates that both inflow and outflow congestions can reduce the MEFs in clean regions during specific periods. In the outflow congestion case, renewable generation could be on the margin in the clean region, leading to curtailments and zero marginal emissions rate. In the inflow congestion case, the marginal emissions rate in the West could be lower when natural gas generation in the West is displacing coal generation in the East. The congestion will affect the merit order such that a less cost-effective power plant will be dispatched to meet electricity demand. However, a less cost-effective power plant is not necessarily more polluting (e.g. coal and natural gas).

Due to simplifying assumptions of generation resources and fixed renewable generation, the West load can solely determine the congestion status in our numerical example. In reality, the congestion status at a particular time will be determined by both regional electricity demands and renewable generations. In addition, it is worth noting that, other than congestion, factors such as changes in fuel prices may also affect the merit order of the electricity supply.

2.2.2 The Environmental Values of DERs

DER technologies, especially rooftop solar panels, are expanding rapidly worldwide, and it is critical to understand how these resources will impact emissions from the electricity sector (SEIA 2022). In particular, understanding the environmental value, as a vital component of the total economic values of DER technologies, plays an essential role in designing subsidization and compensation policies for such technologies.

To promote the adoption of rooftop solar panels, more than 40 US states have implemented net-metering policies that compensate for net generation from rooftop solar at the prevailing retail price of electricity (Brown and Sappington 2017b). However, several states have transitioned from this traditional net-metering policy towards an avoided-cost-based rate reflecting rooftop solar's time-varying economic values (NCCETC 2023). The main reason for this transition is to eliminate the cross-subsidization concerns in the traditional net-metering policies (NCCETC 2023).[7] For example, the State of Minnesota implemented the value of solar (VOA) tariff in 2014 as an alternative to the net-metering policy, which seeks to quantify the real value of rooftop solar based on avoided costs (Minnesota Department of Commerce 2014). Similarly, the New York State Public Service Commission (NYSPSC) established the Value of Distributed Energy Resource (VDER) in 2017 as a new mechanism to compensate for electricity generation from DERs (Bowen et al. 2022).

In these new tariffs, the compensation rate for DERs is generally composed of three main components: avoided energy cost, avoided capacity cost, and avoided environmental cost. The avoided environmental costs of carbon are calculated by multiplying the social cost of the carbon ($ per tonne) by its estimated marginal emissions rate (tonnes per MWh).[8] Depending on the social costs of carbon and location, the avoided environmental costs can account for 10% to 20% of the current DER compensation rate and are expected to increase as the social cost of carbon rises (Hochul and Seggos 2023; Energy Sage 2023b). The marginal emissions rates used to calculate the avoided environmental costs are kept fixed by the authorities to avoid complications for the DER customers (Bowen et al. 2022). For example, the NYSPSC uses the average MEFs as the marginal emissions rate even though the MEFs are estimated for each hour of the day and each month of the year (Bowen et al. 2022). Further, the avoided environmental cost is locked for 25 years, meaning a customer will be given the same environmental credit for every kWh he supplied to the grid for the entire

7. It is worth noting that a relatively "simple" solution is to price DERs based on the locational marginal prices, coupled with a carbon pricing mechanism. However, in practice, customers are not subject to these price signals.

8. Other pollutants, such as NOx, are calculated using the same method but account for less than 3% of the avoided environmental costs (Minnesota Department of Commerce 2014). Therefore, our paper focus on the environmental value of DERs resulting from carbon mitigation.

lifecycle of the solar panel, regardless of when and where the power is generated (Minnesota Department of Commerce 2014; Bowen et al. 2022).

As shown in section 2.2.1, congestion can affect the marginal emissions rate based on location and time, leading to different environmental values of DERs in different locations. A solar project can reduce more emissions if it is located in a region where the marginal emissions rate during solar generating hours is high. Similarly, battery storage has a higher potential to reduce emissions if it is located in a region where the marginal emissions rate during battery charging and discharging spreads more extensively. In our numerical example, a solar panel can reduce more emissions if it is located in the East. However, a battery system can reduce more emissions if it is located in the West due to the higher MEF difference with and without congestion. Therefore, it is essential to consider DER's locational MEFs and locational environmental values when designing DER compensation policies.

Apart from the direct environmental impact of MEFs, a DER technology can alleviate congestion, indirectly affecting their environmental outcomes. For example, a battery can alleviate congestion by discharging power when the system is congested. Developing a dispatching model based on merit order in both regions is necessary to estimate these indirect effects. However, this is out of the scope of the current analysis. Our study will focus on the direct environmental impact of the MEFs.

2.3 Texas's Electricity Market

The wholesale electricity market in Texas is operated by The Electric Reliability Council of Texas (ERCOT), which covers 75% of Texas's land area and serves about 90% of Texas's electric load (ERCOT 2022; 2023a).

ERCOT optimizes energy dispatch using a security-constrained economic dispatch

(SCED) model, which provides the least-cost energy dispatch subject to the grid's transmission constraint. The real-time SCED model calculates the nodal locational marginal prices (LMPs) every 5 minutes for thousands of specific locations in the electricity grid based on the network's real-time transmission constraints. The LMPs in ERCOT comprise of real-time wholesale electricity prices and congestion costs. The LMPs reflect the value of electricity at different locations in the grid and are designed to motivate efficient location of new generation and transmission investments. Unlike many other jurisdictions in the US, as of 2023, the marginal transmission system losses (line losses) have not been incorporated into the LMP mechanisms in ERCOT (Potomac Economics 2024). Therefore, when the system is uncongested, the LMP in each node will converge to a uniform price. When congestion arises, the LMPs will increase in regions where power in-flow is constrained and decreases in regions where power out-flow is constrained (Brown et al. 2020).

Texas is the leading state in the US in terms of electricity generation, accounting for 12.3% of all electricity production in the US (EIA 2023). Natural gas power plants are the backbone of the generation resources in Texas, accounting for 42% of all electricity generation in 2021. Renewable energy resources, especially wind, are essential in ERCOT's generation mix, with more than 20% of electricity generation from wind and another 4% from solar. The share of electricity generation from coal has dropped significantly in the last decade, from 40% in 2011 to 19% in 2021 (EIA 2023).

Texas leads the US in wind generation, but its current electricity infrastructure cannot transmit or store all electricity generated from renewable energy resources, resulting in frequent curtailment of renewables (Potomac Economics 2023b). ERCOT divides its territory into four major load zones: West, South, North, and Houston (see Figure 2.3). Load zones are designed so that electricity transmission faces fewer limitations within zones than across zones (Fell et al. 2021). The wind energy resources are mainly located in the West and South zones of ERCOT, away from the population centers in the North and Houston areas. As a result, part of renewable generations will have to be curtailed when facing transmission constraints between distant wind farms and large population centers. During our sample period, about 12 TWh of wind power have been curtailed, accounting for 3% of all wind generation. However, with more wind projects being developed in recent years, wind curtailment reached 5% in 2021, and the trend is expected to continue without substantial investment for transmission upgrades. Most solar projects are also located in the West zone, and solar energy accounts for 15% of all electricity generation in the West. With rapidly expanding solar projects in Texas, solar curtailment also increases rapidly. In 2021, 10% of all solar energy had been curtailed (Potomac Economics 2023b).

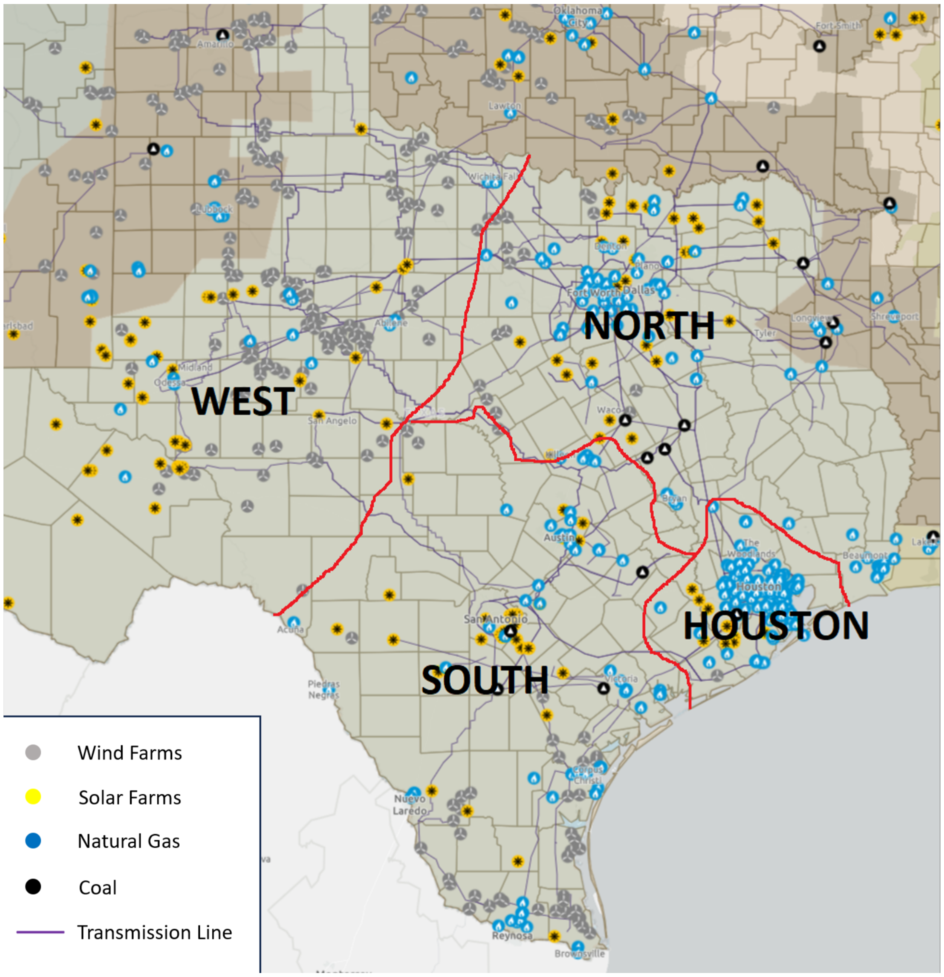

Figure 2.3: Generation and Transmission Infrastructures in ERCOT Load Zones

Source: EIA Energy Infrastructure and Resources Maps

As the West and South zones have the highest share of wind generation, more than 90% of renewable curtailment occurs in these areas due to transmission congestion between or within the two zones (BTU Analytics 2023). The curtailment is more evenly distributed across all wind farms in the West zone, as the transmission bottleneck occurs mainly across zones between the West and the South. In contrast, in the South zone, six wind projects account for more than half of the curtailments, which implies that transmission congestion within the South zone plays a significant role in renewable curtailment (BTU Analytics 2023).

2.4 Data

To perform our analysis, we collect hourly data on load, generation, emissions, weather conditions, and LMPs in ERCOT between 2017 and 2022.[9] This period is particularly interesting due to the rapid expansion of wind energy resources and frequent wind curtailments due to system congestion. During the sample period, ERCOT added approximately 2,000 miles of new transmission lines to the grid system, representing a 4% expansion of the electric grid system in 2017 (ERCOT 2023b).[10]

To construct a measure for congestion status in each load zone in ERCOT, we collect the 15-minute zonal-level LMPs from ERCOT's real-time market for each load zone. The zonal-level LMPs are calculated by taking the load-weighted average of all nodal LMPs within a given load zone. The LMPs will converge to a uniform price when congestion does not occur. Therefore, the spread of different zonal LMPs can reflect the shadow price of constraints and serve as an indicator of congestion status across load zones. Section 2.5.1 provides more details on how we use LMPs to measure congestion.

To calculate the MEFs, we first collect emissions data from the Environmental Protection Agency (EPA)'s Continuous Emission Monitoring System (CEMS). CEMS provides hourly emissions data for each fossil-fuel generator with a capacity of 25 MW or higher in the US (EPA 2023a). To assign carbon emissions from a generator to a specific load zone in ERCOT, we use the EIA-860 survey provided by the EPA to pair each generator in Texas from the CEMS to a specific county. The EIA-860 survey collects detailed information for each generator in the US with a capacity of 1 MW or higher (EIA 2023). Then, we use the load zone map provided by ERCOT to assign each generator to a load zone based on its

9. ERCOT does not publish data on renewable curtailments, so we cannot construct congestion measures based on curtailments.

10. For reference, the CREZ (Competitive Renewable Energy Zones) project, conducted from 2005 to 2013, added 3,600 miles of transmission lines (ERCOT 2014). The purpose was to connect renewable-rich regions to population centers (ERCOT 2014).

location.

The CEMS only contains generation data for fossil fuel generators. To control for renewable generation, we collect ERCOT-wide hourly generation data for wind and solar resources from ERCOT's annual Fuel Mix Report (ERCOT 2023a). To obtain the zonal-level renewable generation estimates, we collect the most recent hourly zonal-level renewable generation data from ERCOT's Intermittent Renewable Resources data.[11] We then regress the zonal-level renewable generation data on ERCOT-wide generation, and estimate the zonal-level renewable generation based on the regression model. To control for shifts in electricity demand, we collect hourly load data from ERCOT at the ERCOT and zonal levels (ERCOT 2024).

Finally, to use as potential instruments for congestion status, we collect weather station data in Texas using National Centers for Environmental Information's Integrated Surface Dataset (ISD). The ISD contains hourly weather data for over 35,000 stations worldwide and 197 weather stations located in Texas (NOAA 2023). The dataset covers a wide range of climate data, including temperatures, wind speed, and wind directions. A comprehensive discussion on constructing instruments for congestion status using weather station data is provided in Section 2.5.2.

To evaluate the environmental values for solar panels, we collect solar irradiation data from the National Renewable Energy Laboratory (NREL)'s Typical Meteorological Year version 3 (TMY3) data sets (NREL 2014). The TMY3 dataset provides hourly solar irradiation data for 1,020 locations throughout the US. The irradiation data from this dataset allows users to compare the performances of solar panels of different configurations and locations. For comparability, we use the normalized solar panel output based on the average solar

11. We are unable to obtain historical data from ERCOT, as it only retains a 7-day record for load-zone-specific wind and solar generation data. As a result, we only acquired zonal-level renewable generation data for February 2024.

irradiation in Texas to calculate the solar output from a rooftop solar.

Table 2.1 summarizes the hourly carbon emissions, hourly electricity load, and hourly LMPs for each load zone and hourly renewable generation in ERCOT. On average, the West zone accounts for 10% of the load in ERCOT but only emits 3% of carbon emissions due to the high penetration of wind and solar. The lowest hourly emissions in the West zone is 0, indicating that renewable energy generation 100% covers the West load. However, the average LMPs in the West are higher than other load zones due to very high LMPs in times with inflow congestion and low renewable outputs.

2.5 Methodology

This section presents the methodology used in this study. In section 2.5.1, we present two measures for the congestion status: an ERCOT-wide congestion measure and a load-zone-specific congestion measure. In section 2.5.2, we present two empirical strategies to examine the effect of congestion on MEFs. We first look at how ERCOT-wide congestion affects the ERCOT-wide MEFs. Then, we use an endogenous regime-switching model to investigate how load-zone-specific congestion will affect the locational MEFs of the corresponding load zone.

2.5.1 Congestion

We measure the congestion status of ERCOT based on its zonal-level LMPs in the real-time market, which is calculated by taking the average of all nodal-level LMPs in a load zone. The LMPs in ERCOT are comprised of wholesale electricity price and congestion cost. When congestion arises, the LMPs will increase in regions where power in-flow is constrained and decrease in regions where power out-flow is constrained (Brown et al. 2020). Therefore,

Table 2.1: Summary Statistics

	Units	Mean	Std. Dev.	Min	Max
Hourly ERCOT CO_2	Tonnes	22,475.2	7,126.4	7,435.4	61,761.4
Hourly West CO_2	Tonnes	672.2	331.9	0	2,153.4
Hourly South CO_2	Tonnes	5,160.1	1,952.1	931.3	15,754.0
Hourly North CO_2	Tonnes	10,974.4	3,829.8	2,065.5	29,566.4
Hourly Houston CO_2	Tonnes	5,668.5	1,545.8	2,732.9	14,482.0
ERCOT Load	MWh	43,221.1	9,739.0	25,566.1	80,037.8
West Load	MWh	4,483.2	827.3	2,372.6	7,922.7
South Load	MWh	10,468.3	2,661.5	5,964.0	20,127.7
North Load	MWh	17,977.3	4,537.7	10,212.7	35,221.3
Houston Load	MWh	12,349.2	2,710.6	7,422.6	22,014.0
West LMP	$/MWh	41.37	259.40	-31.65	9,299.49
South LMP	$/MWh	38.50	256.22	-38.73	9,235.13
North LMP	$/MWh	35.80	256.75	-58.52	9,304.38
Houston LMP	$/MWh	37.69	257.53	-31.65	9,226.05
Average Wind Direction	Degree	186.5	89.6	10	360
Average Wind Speed	km/h	37.3	15.2	6.3	108.1
Average Temperature	°C/°F	19.7/67.5	8.6/47.4	0.4/32.7	39.5/103.1
Hourly Solar Generation	MWh	725.6	1,371.7	0	10,248.7
Hourly Wind Generation	MWh	8,782.3	4,846.6	0	26,806.6

we can use the zonal-level LMP spread across regions to measure the congestion status in a system (Fell et al. 2021).[12] We first measure the overall congestion status in the entire ERCOT territory. Then, we measure the congestion status for each of ERCOT's load zones.

We create a binary indicator $Congest_t$ that equals one when congestion arises at time t, equals zero if otherwise. For the ERCOT-wide congestion status, we define $Congest_t = 1$ if the LMP difference between any two load zones exceeds some cutoff value. We use \$5 as our baseline cutoff value, which strongly indicates the system is congested. Alternative cutoff values of \$1 and \$10 are examined in the robustness checks.

Using our baseline specification, we find that from 2017 to 2022, the system in ERCOT was congested 38% of the time.[13] Figure 2.4 presents the average percentage of congestion occurrence by the hour of the day. Congestion frequently occurs at all hours of the day but is more likely to occur during high-demand hours around 4:00 PM. The congestion status varies across years due to both renewable penetration and transmission expansion. Particularly, increased penetration of renewables has led to higher levels of congestion in ERCOT. Appendix F presents the evolution of congestion status over the years.

12. A wider zonal-level Locational Marginal Price (LMP) spread can usually indicate a more severe congestion status between two load zones. For example, when a load zone faces congestion at just one of its nodes, the zonal-level LMP spread tends to be low. In contrast, when congestion occurs at the bottleneck between two load zones, all nodes within the congested zone will have either lower or higher LMPs than the uncongested zone.

13. Under alternative cutoff values of \$1 and \$10, the ERCOT system will experience congestion for 67% and 17% of the time, respectively. In comparison, ERCOT is congested 42% of the time as measured in Fell et al. (2021). According to Potomac Economics (2023a), from 2018 to 2020, there is at least one binding constraint for more than 70% of the time. As we focus on more severe congestion, the average congestion time in our study is lower.

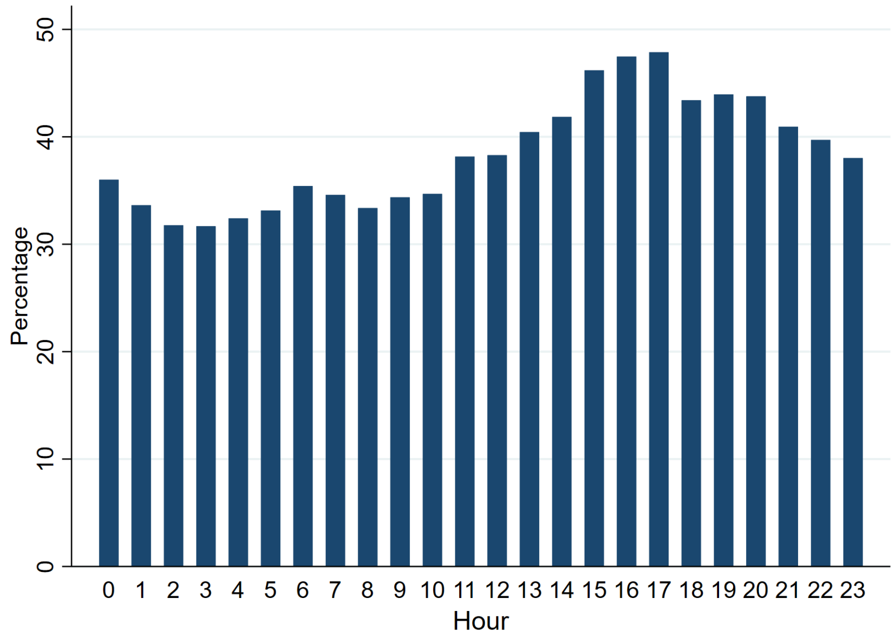

Figure 2.4: Congestion Occurrence by Hour

By examining the data, when the system is congested, a particular load zone tends to have significantly higher or lower LMP than the other zones. We identify the most congested zone and decompose congestion by load zone and power flow types. In particular, a zone is considered "congested" if its LMP and the mean of the LMPs from the other zones have a spread larger than \$5. It is worth noting that two zones could be congested simultaneously under this definition. As mentioned above, if the LMP in the congested zone is lower than the uncongested region, there is an outflow congestion; if it is higher, there is an inflow congestion in the congested zone. The results using the \$5 benchmark are shown in Figure 2.5. During our sample period, the West zone accounts for over 60% of all hourly congestion with both inflow and outflow constraints. In comparison, according to Potomac Economics (2023a), the West zone accounts for around 50% of the congestion in 2019 and 2020, driven by high renewable output. It is not surprising since the West zone is sparsely populated but accounts for around 80% of ERCOT's wind generation.

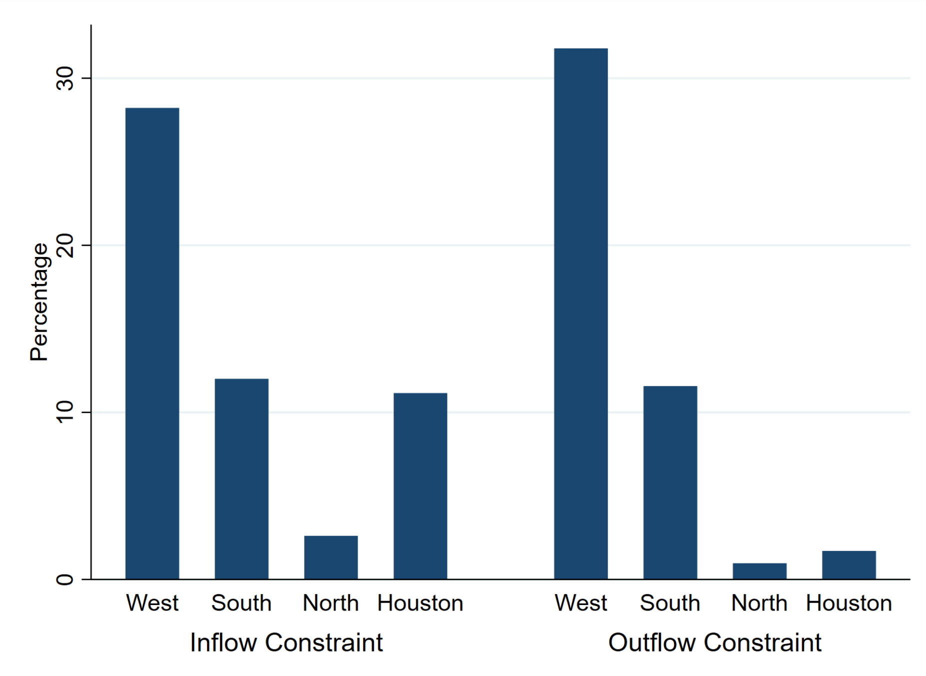

Figure 2.5: Congestion Decomposition by Load Zones

It is worth noting that our congestion measure is based on zonal-level LMPs. The spread of LMPs for each node within the zone is required to differentiate between congestion within and across zones. Unfortunately, nodal-level LMPs from ERCOT are only accessible through an official data request, which we have not pursued due to the associated costs. Therefore, we defer this aspect to future research. As a result, our congestion measure may underestimate the congestion status in a load zone with both inflow and outflow constraints, as the high and low nodal-level LMPs may cancel each other out. As mentioned in section 2.3, congestion occurs frequently within the South zone but less frequently within the West zone. Therefore, our measure for West congestion is relatively accurate.

2.5.2 Empirical Strategy

We use several empirical strategies to investigate how transmission congestion affects marginal emissions in ERCOT. First, we examine how ERCOT-wide transmission congestion will affect the average ERCOT-wide marginal emissions. During periods of congestion, the regional MEFs may increase or decrease depending on the changes in the marginal generators. Accordingly, the average ERCOT-wide MEFs may rise or fall, depending on the relative changes in regional MEFs and the respective demand levels for each subregion.[14] Since ERCOT-wide MEFs do not account for the location and source of the unit increase in electricity demand, this increase will represent the probability of where the demand might originate. Consequently, the average ERCOT-wide MEFs can represent the load-weighted average locational MEFs.

We are interested in ERCOT-wide MEFs because they provide a general picture of how transmission congestion affects marginal and overall carbon emissions. If ERCOT-wide MEFs are higher during periods of congestion compared to uncongested periods, then, on average, meeting a unit increase in electricity demand in ERCOT during congested hours will result in more pollution.

Next, we investigate how transmission congestion of a particular load zone affects each zone's locational MEFs using an endogenous regime-switching model. During uncongested periods, the locational MEFs should be equal to the ERCOT-wide MEFs. However, when congestion arises, the locational MEFs are determined by the marginal generator of the specific load zone. Consequently, the locational MEFs tend to be lower in regions with higher renewable penetration when renewable energy could appear on the margin during congested hours. In contrast, if dirtier sources of electricity generation must be called upon to generate electricity when congestion arises, the locational MEFs will be higher during congested hours.

14. For example, suppose ERCOT has two subregions, West and East. The energy demand in the East and West are 2,000 MWh and 1,000 MWh, respectively. During a congestion, the West MEF is 0 kg/kWh and the East MEF is 0.8 kg/kWh. The average ERCOT-wide MEFs will be the load-weighted average MEFs of the two subregions, which is given by 0*1/3+0.8*2/3=0.53 kg/kWh. Suppose the ERCOT-wide MEF is 0.5 kg/kWh when the system is uncongested. Congestion leads to an average increase of 0.03 kg/kWh in the MEFs.

ERCOT-Wide MEFs

We start by describing the primary empirical strategy we use to estimate the ERCOT-wide MEFs. Adapted from Fell et al. (2021), we estimate the following model:

$$\begin{aligned} E_{hdmy} =& \beta_0 + \beta_1 D_{hdmy} + \beta_2 Congest_{hdmy} + \beta_3 D_{hdmy} \cdot Congest_{hdmy} \\ & + \sum_j \theta_j X_{hdmy} + \gamma_h + \eta_m + \delta_d + \tau_y + \varepsilon_{hdmy} \end{aligned} \tag{2.1}$$

where E_{hdmy} is the total emissions from all fossil fuel power generators located in the ERCOT territory for hour h, day d, month m, and year y. D_{hdmy} is the hourly demand in ERCOT.

$Congest_{hdmy}$ is a dummy variable indicating the congestion status, as described in Section 2.5.1. $\sum_j \theta_j X_{hdmy}$ represents a set of control variables, specifically including the average regional (zonal) temperatures for each load zone, and the total wind and solar generation in ERCOT, with θ_j being the corresponding coefficient for each variable. We include regional temperatures and total renewable generation because they may impact both congestion and emissions, leading to endogeneity concerns. For instance, increased wind generation might raise the probability of congestion while simultaneously lowering overall system emissions. Similarly, changes in regional temperatures may impact regional demand, indirectly influencing ERCOT-wide emissions and congestion status. Consequently, omitting these variables could introduce omitted variable bias.

Finally, γ_h, η_m, and δ_d are dummy variables that stand for the hour of the day, the month of the year, and the day of the week, respectively. We include these time variables to control for unobserved source of variation that may correlate with the electricity demand. To control for long-term factors such as increase in generation and transmission capacities, we include the year dummy variable τ_y. To deal with heteroskedasticity and autocorrelation, we use Newey-West standard errors in this estimation with 24 lags.

If congestion is not considered, β_2 and β_3 are set to zero and β_1 captures the increase in emissions from a 1 MWh increase in ERCOT-wide electricity demand (also known as the average ERCOT-wide MEF). Our coefficient of interest is β_3, which captures the changes in MEF caused by congestion and $\beta_1 + \beta_3$ captures the average MEF in ERCOT when congestion occurs.

The estimated coefficients in Equation (2.1) could be biased if congestion is endogenous, even after controlling for regional temperatures and total renewable generation. For example, endogeneity may arise due to unobserved plant outages that affect both congestion and emissions. Suppose a coal-fired generator is closed for maintenance; this can lead to regional congestion and reduce overall emissions in the jurisdiction. Consequently, this may systematically bias the estimated effects of congestion on emissions downward.

To address this potential endogeneity problem, we employ an instrumental variable approach. Weather conditions such as wind direction, wind speed, and air temperature have been utilized as instruments for congestion in previous studies (Fell et al. 2021; Woerman 2018). Air temperature and wind conditions can influence the transmission capacity of a transmission line because the capacity of a transmission line is constrained by its thermal limit. More specifically, the transmission line is limited by the maximum temperature the conductor can safely reach without risking damage or failure. Cooler air temperatures, higher wind speeds, and a more direct wind direction enhance the cooling of the conductor, thereby allowing the line to carry more current without exceeding its thermal limit.[15] Consequently, during windy and low-temperature days, the transmission line can operate at a higher capacity due to the increased cooling effect.

However, a potential concern in using wind conditions and air temperatures as instruments

15. Both wind speed and wind direction can affect the capacity of a transmission line due to cooling effect (Gentle et al. 2012). In particular, Gentle et al. (2012) find that the wind can increase the transmission capacity by 10% to 40% in Idaho most of the time. Phillips (2014) find that the parallel wind only achieves 40% of the cooling effect compared to the perpendicular wind.

is that they may still affect total emissions through channels other than their impact on congestion, such as electricity demand and renewable generation. To address this concern, we first control for regional temperatures and renewable generation as in Equation (2.1). After controlling for wind generation, the impact of wind speed and wind directions on emissions through wind generation can be teased out, making wind conditions valid instruments for congestion status. Similarly, after controlling for electricity demand, air temperatures should only affect emissions through their impact on transmission congestion. These statements hold true as long as the instruments for congestion are uncorrelated with the error term after controlling for demand and renewable generation (Wooldridge 2010).[16]

In addition, to ensure that air temperatures and wind conditions affect emissions solely through their impact on transmission congestion, and to ensure that these instrumental variables are not weak, we can choose air temperatures and wind conditions from certain locations as instruments. Specifically, the selected air temperatures and wind conditions should be correlated with congestion status but should not influence emissions through channels other than congestion after controlling for regional temperatures and total renewable generation.

It is reasonable to assume that some unobservable confounding factors, such as local demand, will only be affected by local weather conditions. In other words, only weather conditions near large load centers (e.g., metropolitan areas) or wind and solar farms may influence emissions through effects on local demand or renewable generation. However, given the complexity of the power grid, the likelihood of transmission congestion may change due

16. It is important to consider that wind speed, temperature, and wind direction may also influence plant outages. For example, extreme weather conditions, including high winds and low temperatures, may contribute to operational issues or force outages at power plants. However, these factors are generally considered less likely to directly impact the specific relationship between congestion and emissions compared to their effects on transmission capacity. Despite this, weather conditions remain a valid choice for instrumental variables because they provide exogenous variation in congestion. The use of these weather-related instruments is supported by their demonstrated ability to affect transmission capacity without directly influencing emissions through other channels under normal weather conditions.

to weather conditions at various locations near the transmission system. Therefore, it is possible to identify weather conditions from locations far away from demand centers and wind farms that are correlated with the congestion status and use them as potential instruments. Therefore, after teasing out the effects of renewable generation and demand on emissions, changes in wind speed, wind direction, and air temperatures at these weather stations can only affect emissions by changing the transmission capacity of the transmission system. Finding exact weather conditions that meet these criteria can be challenging without first obtaining geographic data on locational demand and renewable generation. However, we can use a large set of weather conditions data from across Texas as instruments to avoid, or at least alleviate, the potential effects of local weather conditions on local emissions (Woerman 2018).

Following Belloni et al. (2012), we first employ an IV-LASSO (least absolute shrinkage and selection operator) method to choose a set of informative instruments from a large set of variables. These variables include wind conditions and air temperature data collected from more than 200 weather stations in Texas. Furthermore, we include a set of interactions between the weather conditions data from the weather stations with a set of control variables at the ERCOT level and zonal level, including the ERCOT-wide load, the renewable generation at the ERCOT level, and the average regional temperatures. This IV-LASSO procedure aims to identify a subset of weather conditions that are more likely to affect the likelihood of congestion. Figure 2.16 in Appendix E displays a map of all selected weather stations in Texas.

Next, we proceed with a standard two-stage IV estimation using the selected set of instruments. In particular, our excluded instruments include wind speed, wind direction, and air temperatures information from selected weather stations in the IV-LASSO procedure, as well as the selected interactions between weather conditions and the control variables. In the first stage, we utilize the selected variables to predict congestion and the interaction term between congestion and demand. In the second stage, we employ the fitted values from the first stage as instruments for congestion and the interaction term. We include renewable generation and zonal temperatures as control variables in both stages to ensure that the instruments are valid.

Because we need to control for renewable energy generation to obtain valid IV estimators, the MEFs we obtained from Equation (2.1) will not include the case where renewable energy resources are on the margin.[17] Although wind and solar will not be on the margin system-wide in ERCOT because the system demand is always higher than renewable generation in our sample period, solar and wind can be on the margin in certain areas, as indicated by the overall renewable curtailments. Unfortunately, measuring how this will impact ERCOT-wide MEFs is difficult without obtaining nodal-level data.[18] As a result, when renewable is on the margin, the system-wide MEFs can be lower than we estimated in Equation (2.1).[19]

To obtain hourly MEFs, we modify Equation (2.1) by adding hourly dummies to the demand-congestion interactions based on Graff Zivin et al. (2014). Formally, we estimate the following model:

---

17. Because wind and solar will not be on the margin without congestion, the average MEF when renewable energy resources are on the margin can be captured by the congested MEF ($\beta_1 + \beta_3$) plus the coefficient of wind or solar. Since wind and solar are clean energy resources, the average MEF when wind and solar are on the margin is expected to be zero.

18. Appendix A provides a detailed discussion on this matter and how to estimate the average system-wide MEF using nodal-level LMPs.

19. As a simple illustration, suppose the ERCOT-wide MEF we estimated is 0.6 kg/kWh when the system is congested. This implies that when ERCOT-wide demand increases by 1 kWh, emissions increase by 0.6 kg when a non-renewable generator is on the margin to meet the demand increase. Suppose that the West is congested, and wind is on the margin in the West. The 1 kWh demand increase could partially originate in the West. On average, the likelihood that the demand increase originated in the West can be approximated by the size of the demand in the West. Suppose that there is a 50% chance that the demand increase originated from the West whenever congestion occurs; the renewable-adjusted ERCOT-wide MEF should be 0.3 kg/kWh. This exercise further highlights the importance of regional MEFs.

$$
\begin{aligned}
E_{hdmy} =& \beta_0 + \sum_{h=0}^{23} \beta_{h1} D_{hdmy} + \beta_2 Congest_{hdmy} \\
&+ \sum_{h=0}^{23} \beta_{h3} D_{hdmy} \cdot Congest_{hdmy} + \sum_{j} \theta_j X_{hdmy} + \eta_m + \delta_d + \varepsilon_{hdmy}
\end{aligned}
\tag{2.2}
$$

Equations (2.1) and (2.2) explore how congestion will affect MEFs in ERCOT. However, congestion can affect regional MEFs differently depending on regional energy resources. In order to understand how transmission congestion affects the locational environmental value of DER technologies, we need to measure the marginal emissions rate at each location and in each hour when congestion arises.

Locational MEFs

Estimating locational MEFs is different from estimating ERCOT-wide MEFs. When the system is uncongested, both locational MEFs and ERCOT-wide MEFs can be estimated based on ERCOT-wide load and emissions. This is because any generation units located in ERCOT can respond to changes in local demand. However, once a region is congested, only local generators can be used to meet the marginal demand. Effectively, the locational MEFs are determined in two regimes: an uncongested regime where MEFs are based on ERCOT-wide load and emissions and a congested regime where MEFs are based on local load and emissions. As a result, the endogenous regime switching model is an appropriate solution to estimating locational MEFs.

Regime-switching models have been widely used in the analysis of transmission congestion in electricity markets (Sapio 2015). However, it has not yet been used to answer how congestion will affect marginal emissions. There are two main advantages of using an endogenous regime-switching model in the analysis of congestion. First, compared to traditional econometric models that include congestion indicators as dummy variables, the endogenous regime switching model exhibits better forecasting performances and consistency (Fabra and Reguant 2014; Gianfreda and Grossi 2012). Second, the endogenous regime-switching model uses the instrumental variable approach to describe the switching process, which helps to deal with the endogenous nature of congestion.

In an endogenous regime-switching model, the data generating process is switching between two states, and the switching process is determined by a criterion function (Chang et al. 2017). When the state variable is endogenous, the model is estimated using the instrumental variable approach as described by Maddala (1983). Formally, the criterion function can be given as follows:

$$C_t = \begin{cases} 1 & \text{if } Z_t\eta + u_t > 0 \\ 0 & \text{if } Z_t\eta + u_t \leq 0 \end{cases}$$

where $C_t = 1$ when there is congestion (ERCOT-wide or zonal-level), and $C_t = 0$ otherwise. Z_t is a vector of potential instrumental variables used for the congestion indicator. We use the same IV-LASSO procedure to select instrumental variables for each load zone in ERCOT as in the ERCOT-wide case.[20]

η is a vector of parameters and u_t is the Gaussian error term. Formally, we estimate the following equations in order to capture the hourly MEFs in each region:

$$\text{Uncongested: } E_t = \beta_1 + \sum_{h=1}^{24} \beta_{2h} H_h D_t + \sum_j \theta_j X_t + \varepsilon_t \text{ if } C_t = 0 \tag{2.3}$$

$$\text{Congested: } E_{it} = \beta_3 + \sum_{h=1}^{24} \beta_{4ih} H_h D_{it} + \sum_j \theta_j X_{it} + \varepsilon_{it} \text{ if } C_t = 1 \tag{2.4}$$

20. Similar to the previous case, we select the most relevant variables from a large set of variables such that the variables can best "predict" zonal congestion. The variables include weather conditions (local wind speed, local wind direction, and local temperature) for over 200 weather stations in Texas, ERCOT-wide and zonal renewable generation, and ERCOT-wide and zonal load.

where E_t is the hourly emissions from all fossil fuel power generators located in the ERCOT territory. E_{it} is the hourly emissions from all fossil fuel generators from load zone i. D_t measures the hourly demand in ERCOT. D_{it} measures the hourly demand in load zone i. H_h are dummy variables for hour h of the day. X_t is a set of control variables for the month of the year, day or the week, system or zonal-level renewable generation, and system or zonal-level temperatures. The hourly MEFs when the system is uncongested are captured by β_{2h}, whereas the hourly MEFs when the load zone i is congested are captured by β_{4ih}.

The endogenous regime switching model described above is estimated using the maximum likelihood method (Lokshin and Sajaia 2004). The Huber-White sandwich estimator is used to obtain heteroskedasticity-consistent standard errors.

Similarly to the ERCOT-wide case, to ensure that the variables are valid instruments, we control for temperatures and renewable generation at each load zone. Therefore, wind conditions should only affect emissions through their impact on transmission congestion. Additionally, by using weather condition data from over 200 weather stations across Texas, we can select weather stations in specific locations as instruments. In particular, because only local temperatures will affect local demand and local emissions, we can use temperatures from locations across Texas as instruments to avoid local effects. Thus, after controlling for local demand and local renewable generation, the instrumental variables will only affect emissions through their impact on congestion.

The above estimating equations reflect the assumption that when a load zone is congested, it becomes an independent grid island. The actual congested area could be any subset of the ERCOT territory, which unfortunately cannot be observed without nodal-level data. As described in Section 2.5.1, we use two methods to measure the congestion status: a system congestion status and a load-zone-specific congestion status. In this case, using the load-zone-specific congestion measure is more appropriate as it more accurately reflects the case when a load zone becomes independent.

Because we have included renewable generation in the estimation of Equations (2.3) and (2.4), the locational MEFs will only capture cases where renewable energy resources are not on the margin. To capture the case when renewable energy resources are on the margin in a load zone, we calculate the average time that a zone has a negative zonal-level LMP. A negative zonal-level LMP indicates that most nodal-level LMPs in the load zone are negative, and renewable energy is on the margin for these nodes. Similarly to the ERCOT-wide case, there are times when wind and solar energy are on the margin in a limited area (covering a few nodes) in a load zone. To properly account for these cases, nodal-level data is required. A discussion on how to use nodal-level LMPs to address these cases is provided in Appendix D. Due to data limitations in our study, we leave this for future work.

2.6 Results

This section presents the locational MEFs identified in this paper. We first present how transmission congestion will affect the ERCOT-wide MEFs. We then focus on three load zones in ERCOT (West, North, and South) to show how congestion will affect the locational marginal emissions.[21]

2.6.1 ERCOT-Wide Marginal Emissions

We first investigate how congestion will affect the MEFs in ERCOT in general. Using our benchmark congestion measure described in section 2.5.1, we estimate Equation (2.1) and present the results in Table 2.2. The coefficient on ERCOT load (β_1) measures the average

21. We exclude the Houston zone for two reasons. First, it is not directly adjacent to the West zone, which is the primary zone we are interested in. Second, the area is relatively small compared to other load zones, and the resulting congestion measure is more likely to be affected by local weather conditions, threatening the validity of our instrumental strategy.

MEFs when the system is uncongested. The average MEFs during congested hours can be obtained by summing β_1 and the interaction term between congestion and load (β_3). Column (1) presents the most common way of estimating MEFs, without considering the effects of congestion. Column (2) presents a simple specification with congestion, which only includes the time controls. Column (3) adds renewable generations as covariates. Column (4) adds linear and polynomial controls for Texas's average heating and cooling degree days.

As shown in Table 2.2 column (1), when congestion is not considered, the average ERCOT-wide MEFs is 0.485 kg/kWh. As a comparison, Holland et al. (2022) estimated the average MEFs in Texas in 2019 as 0.454 kg/kWh. The coefficient on load in column (2) is similar to that of column (1), but once the system is congested, the average MEFs will increase by 0.029 kg/kWh. However, as wind generation can affect both total carbon emissions and congestion status, the coefficients in column (2) can be biased. Columns (3) and (4) provide more reliable coefficients by including additional covariates. As shown in the columns (3) and (4), the positive interaction between congestion and load indicates that the marginal emissions are slightly higher in congested hours than in uncongested hours. The MEF measure in column (4) is higher than that in column (3) due to the inclusion of temperature control, as the overall effects of temperature on emissions is negative.[22] Using column (4) as our preferred specification, we find that congestion can increase ERCOT-wide MEFs by around 3.1%. This indicates that when the system is congested, more polluting units will be dispatched following the changes in the merit order. In particular, after controlling for both solar and wind generation, changes in MEFs reflect the tendency for more polluting fossil fuel generators to replace relatively cleaner fossil fuel generators during congested hours. The congestion variable is negative and significant, implying that although the MEFs during congested hours are slightly higher, the average emissions factors are similar during both

22. This negative correlation between carbon emissions and temperature, after controlling for demand, congestion, and renewable generation, likely captures the non-linear relationship between temperature (demand) and emissions.

congested and uncongested hours.[23]

The results using IV-LASSO are presented in Table 2.3. The IV-LASSO procedure leads to a larger effect of congestion on marginal emissions. In the IV-LASSO setting, the congestion will increase ERCOT-wide MEFs by 14.3% based on column (3), which is our preferred model specification. There are two possible reasons why the IV estimates are larger than the OLS estimates. First, the congestion status measure could be endogenous, leading to biased OLS estimates. This could be due to inadequate controls for wind in the OLS setting, caused by different locational effects of wind.[24] Without information on whether the wind has been curtailed, it is difficult to distinguish whether wind or natural gas is on the margin. When the wind speed in a certain region is positively correlated with the probability that the wind is causing the congestion, it will cause a negative bias in the OLS estimator. Using wind speed and temperature at different locations as instrumental variables, we correct the potential bias in the OLS setting.

Second, the higher IV estimates could happen due to the local average treatment effect differing from the overall average effect. This can lead to higher estimates if the variations in congested hours captured by the instruments are prone to hours with higher marginal emissions. For example, this could be the case if higher air temperatures increase the likelihood of congestion, and if higher air temperatures correlate with hours of higher marginal emissions because of renewable curtailment.

Next, we investigate the MEFs for each hour of the day by estimating Equation (2.2)

23. Average emissions factors (AMFs) are calculated by dividing total emissions by total load. Based on the average ERCOT load of 43,000 MWh, the difference in total emissions between congested and uncongested hours, based on column (3) from Table 2.2, is $0.013 * 43,000 - 509.6 = 49.4$, or 0.001 kg/kWh.

24. For example, higher wind speeds near wind farms can increase wind generation, thereby reducing ERCOT-wide carbon emissions by displacing fossil fuel generators. However, higher wind generation can also cause more severe transmission congestion when the power flow exceeds transmission capacity. Additionally, higher wind speeds near transmission lines can increase the capacity of those lines, lowering the probability of congestion. In our case, wind speed in certain areas (e.g., west) can be positively correlated with increased MEF during congestion because when the wind, instead of natural gas, is on the margin, congestion would induce more emissions.

Table 2.2: Effect of Congestion on ERCOT-Wide Marginal Emissions - OLS Estimates

	(1) Carbon Emissions (kg)	(2) Carbon Emissions (kg)	(3) Carbon Emissions (kg)	(4) Carbon Emissions (kg)
Congested×Load (kWh)		0.029***	0.013***	0.017***
		(0.003)	(0.002)	(0.002)
ERCOT Load (kWh)	0.485***	0.478***	0.497***	0.540***
	(0.002)	(0.002)	(0.001)	(0.002)
Congestion		-3522.2***	-509.6***	-786.0***
		(139.2)	(73.5)	(63.7)
Solar Generation (kWh)			-0.479***	-0.589***
			(0.004)	(0.004)
Wind Generation (kWh)			-0.597***	-0.581***
			(0.002)	(0.001)
Constant	-2062.5***	-580.7	3617.0***	2148.7***
	(80.5)	(111.5)	(65.4)	(68.6)
Add Time Controls	Yes	Yes	Yes	Yes
Add Temperature Controls	No	No	No	Yes
Observations	52,577	52,577	52,577	52,577

Notes: This table presents the OLS estimation results of Equation (2.1). The dependent variable is ERCOT-wide carbon emissions. Columns (1) through (4) include different control variables. Time controls include dummy variables for the month of the year, the hour of the day, and the day of the week. Temperature controls include one- to fourth-degree polynomials of heating and cooling-degree days. Std. Dev. in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.3: Effect of Congestion on ERCOT-Wide Marginal Emissions - IV Estimates

	(1) Carbon Emissions (kg)	(2) Carbon Emissions (kg)	(3) Carbon Emissions (kg)
Congested×Load (kWh)	0.204***	0.033***	0.078***
	(0.015)	(0.005)	(0.005)
ERCOT Load (kWh)	0.421***	0.513***	0.548***
	(0.001)	(0.003)	(0.004)
Congested	-18123.2***	-1158.6***	-4856.7***
	(655.4)	(230.3)	(242.5)
Solar Generation (kWh)		-0.489***	-0.512***
		(0.003)	(0.005)
Wind Generation (kWh)		-0.527***	-0.452***
		(0.003)	(0.003)
Constant	7246.6*	3847.7***	3568.5***
	(450.0)	(136.1)	(145.5)
Hausman Test (p-value)	0.0000	0.0000	0.0000
Kleibergen-Paap rk Wald F statistic	46.60	52.99	31.98
Add Time Controls	Yes	Yes	Yes
Add Temperature Controls	No	No	Yes
Observations	41,457	41,457	41,457

Notes: This table presents the second stage of the 2SLS estimation results of Equation (2.1). The dependent variable is ERCOT-wide carbon emissions. Columns (1) through (4) include different control variables. Time controls include dummy variables for the month of the year, the hour of the day, and the day of the week. Temperature controls include one- to fourth-degree polynomials of heating and cooling-degree days. The instruments include weather conditions (wind speed, wind direction, and temperature) from weather stations across Texas and are selected using a LASSO regression. The Stock-Yogo weak identification cut-off at 10% is 10.90. The Kleibergen- Paap rk Wald F statistics suggest that the instruments are not weak. The Hausman test results reject the null that the OLS estimations are efficient. Std. dev. in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

using our IV-LASSO specification in column (3). The results are shown in Figure 2.6. The MEFs during congested hours and uncongested hours with 95% confidence intervals are presented by blue and red colours, respectively. The "System-Wide MEFs" shown in the green line presented MEFs estimations without considering congestion.[25] Compared to Tables 2.2 and 2.3, the hourly MEFs estimated using Equation (2.2) shows a 9.4% difference between congested and uncongested hours. The results suggest that, on average, more polluting sources will be dispatched after congestion. The results highlight the importance of including transmission congestion in estimating MEFs.

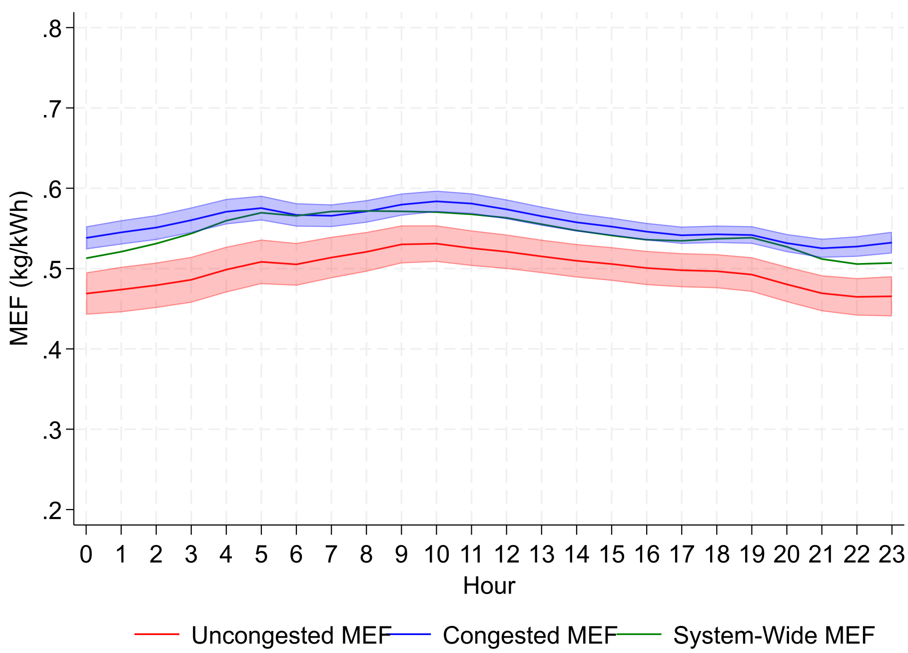

Figure 2.6: Hourly ERCOT-Wide MEFs during Uncongested and Congested Hours

25. Because we have controlled for renewable generations in the estimation of MEFs, this typical "System-Wide MEFs" estimated do not represent the "typical" MEFs reported by other studies. The MEFs in other studies are used to "predict" environmental impacts for load changes that occur at a particular time of the day and therefore do not include control variables. In our study, we must control for renewable generations in order to have valid instruments for congestion. As a result, we include renewable generations in estimating all MEFs to keep them comparable.

2.6.2 Locational Marginal Emissions

In this section, we use the endogenous regime-switching model to estimate the locational marginal emissions in three load zones (North, South, West) in ERCOT. As described in Section 2.2, the location of DER technology can affect carbon emissions through two channels: a direct channel based on locational marginal emissions and an indirect channel based on the shadow environmental value of congestion.[26] Suppose marginal changes in load have minimal impact on congestion status, the locational environmental value of a DER technology will be determined by the locational marginal emissions are estimated in this section.

We first examine how congestion affects the MEFs in the North zone. Figure 2.7 presents the average hourly MEFs of the North zone with 95% confidence intervals during congested and uncongested hours. The green line shows the weighted-average congested MEFs accounting for the hours when wind is on the margin. In particular, the MEFs are weighted by the percentage of hours when renewable energy resources are on the margin.[27] The average MEFs during uncongested and congested hours are 0.579 kg/kWh and 0.543 kg/kWh, respectively. On average, congestion can reduce the MEFs in the North zone by 6.2% as the natural gas generators in the North is relatively cleaner than the ERCOT average. Wind is only on the margin less than 2% of the time, and can reduce the average North MEFs by 0.08 kg/kWh.

26. The shadow environmental value of a transmission constraint represents the marginal change in total emissions resulting from relieving the transmission constraint by one MW. A less constrained electric grid can reduce renewable curtailments and often leads to fewer carbon emissions. Since DER technologies can be used to alleviate transmission congestion, they can indirectly affect carbon emissions.

27. For example, during a given hour, if wind power is on the margin with a 5% probability when the load zone is congested, the weighted-average MEFs for that hour will be 0.95 times the estimated congested MEFs.

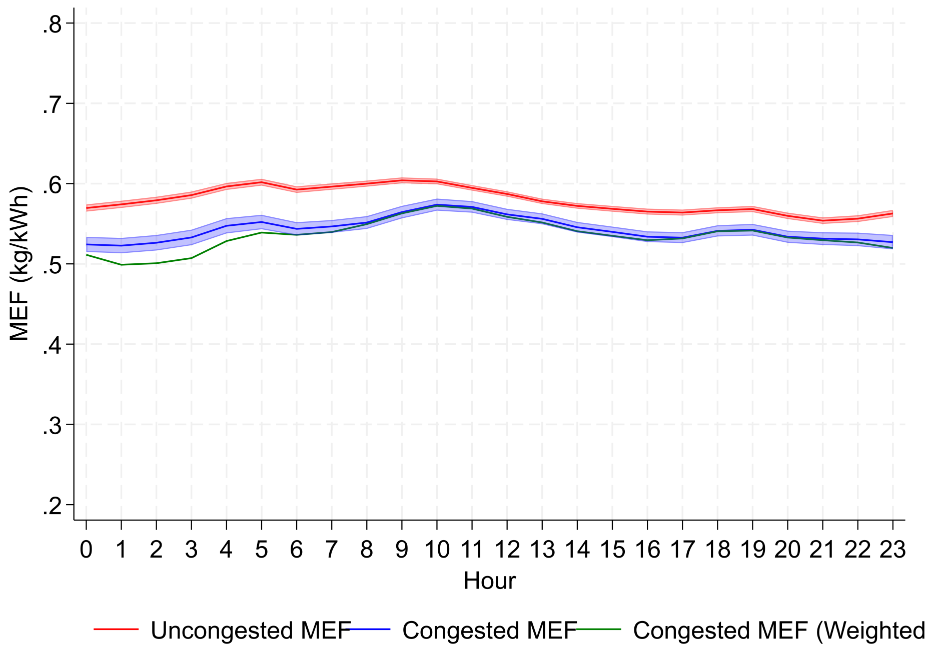

Figure 2.7: MEFs in the NORTH Zone During Uncongested and Congested Hours

As shown in Figure 2.8, the South zone MEFs differ from the North zone as the fossil fuel generators in the South that are more likely to be called upon for generation tend to have higher emissions intensities. In particular, coal generators are more likely to be on the margin in the South, as indicated by the relatively higher MEFs in the mornings. The average MEFs during uncongested and congested hours are 0.599 kg/kWh and 0.736 kg/kWh in the South zone, respectively. This means congestion increases average South MEFs by 22.6%. Similar to the North, wind energy only has a small effect on average MEFs, which reduces average South MEFs by 0.15 kg/kWh.

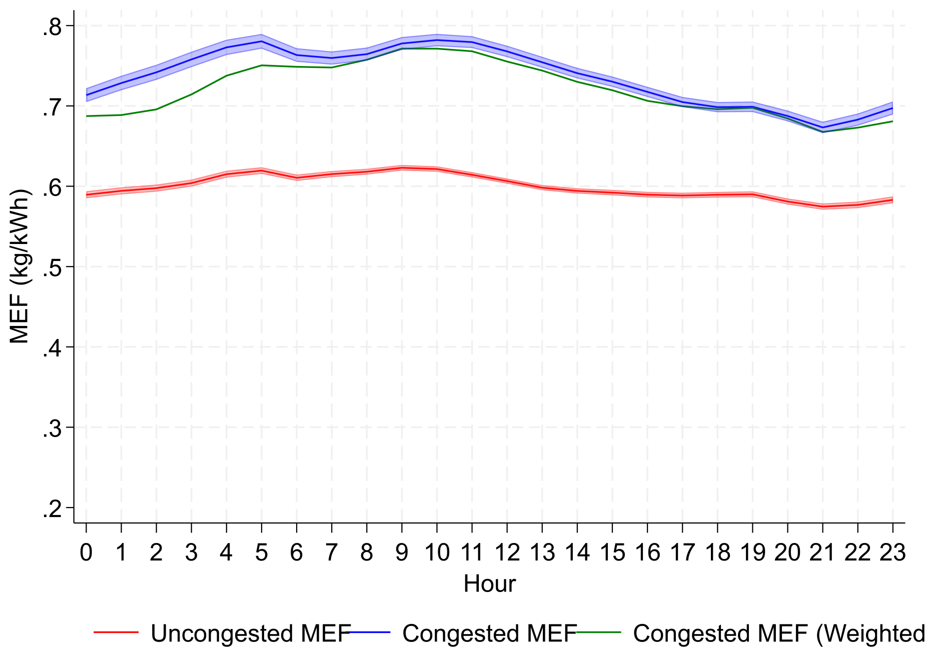

Figure 2.8: MEFs in the South Zone During Uncongested and Congested Hours

The renewable-rich West zone is frequently congested. As shown in Figure 2.9, congestion significantly impacts the MEFs in the West zone. The average MEFs during uncongested hours is 0.588 kg/kWh compared to 0.393 kg/kWh during congested hours. There are two reasons for the low MEFs in the West. First, wind energy resources are deployed on the margin during congestion. In our sample period, negative and zero LMPs (when the wind energy is on the margin) in the West occur in 7.0% of all hours and 15.1% of all congested hours. Second, cleaner natural gas units in the West may substitute dirtier technology in the other regions. The results suggest that congestion can significantly impact DER technologies in the West. Thus, using "typical MEFs" to evaluate the environmental values of DER technologies without considering the impact of congestion will lead to substantial biases.

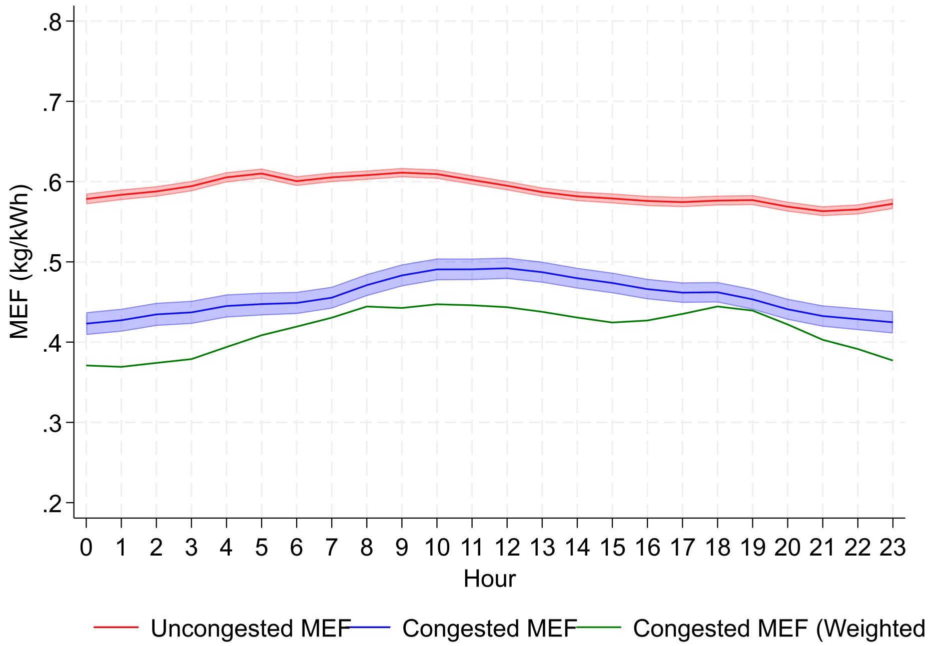

Figure 2.9: MEFs in the West Zone During Uncongested and Congested Hours

2.7 Locational Environmental Values

After estimating the locational MEFs, we can calculate the corresponding locational environmental values of solar and storage. The locational MEFs provided by Section 2.5.2 are estimated under two separate regimes: congested and uncongested. We calculate the associated environmental values of the DERs using the following formula:

$$\Delta CO_2 = \sum_m \sum_h \sum_c \Delta Load_{mh} Congest_{mhc} MEF_{hc} \tag{2.5}$$

where m, h, and c stand for the month of the year, hour of the day, and congestion status, respectively. In particular, we consider three congestion status in our study: uncongested, congested with positive zonal LMPs, and congested and with zero or negative zonal LMPs.

As mentioned in the previous section, a zero or negative zonal LMP indicates that renewable energy is on the margin and the MEF is zero. $\Delta Load_{mh}$ is the load changes resulting from solar or battery for a given month-hour. $Congest_{mh}$ is the percentage of times of a congestion status for a given month-hour. MEF_{hc} is the corresponding MEF of hour h under congestion status c. In other words, the environmental values of DERs represent the changes in CO_2 emissions from both regimes (congested and uncongested), weighted by the likelihood of each regime for a given month-hour. It is important to note that by disregarding the monthly variations in load, the above formula can be simplified as:

$$\Delta CO_2 = \sum_{h} \Delta Load_h \sum_{m} \sum_{c} Congest_{mhc} MEF_{hc} \tag{2.6}$$

where $\sum_m \sum_c Congest_{mhc} MEF_{hc}$ represents the congestion-weighted MEFs for each month-hour. Comparing the congestion-weighted MEFs with typical MEFs provides a convenient way for assessing the impact of congestion on MEFs.

In addition to the congestion-weighted MEFs, the DER technologies' technological features and operational patterns can also affect their environmental outcomes. Without loss of generality, we calculate the annual carbon mitigation for a typical 5 kWh solar system and a 13.5 kWh battery. The capacity reflects the average solar and storage installation capacity for small residential and commercial customers (Energy Sage 2023a). We assume that the solar panel has an energy efficiency of 15%, which means that a solar panel can convert 15% of solar power into electricity (Energy Sage 2023a). Based on the monthly average solar irradiation in three major Texas cities (Houston, San Antonio and Dallas), a 5 kWh solar system can generate around 30 kWh in a typical day. We assume that the battery has a round-trip efficiency of 80%, which means that 80% of the power stored in the batteries can be retrieved for discharge.

We assume that the battery is operated to maximize profits by performing energy arbitrage. For simplicity, the battery operations are based on a typical residential time-of-use rate used in Texas, with a peak period between 1 PM and 7 PM on weekdays (Xcel Energy 2023). Under such a retail rate structure, the battery will be fully charged before 1 PM and discharged as soon as 1 PM to minimize energy losses. Solar will reduce carbon emissions based on how much power it generates in each hour of the day and what is the corresponding MEFs. A battery will increase emissions in hours during charging, and decrease emissions in hours during discharging, based on the MEFs during charging and discharging. We use the Distributed Energy Resources Customer Adoption Model (DER-CAM) to simulate the annual carbon emissions decrease (or increase) from using solar and battery. Detailed information on DER-CAM is available in Appendix B from the first chapter.

Based on the locational marginal emissions estimated in Section 2.6, we calculated the congestion-weighted MEFs for the three load zones in ERCOT. The results are presented in Figure 2.10. The average congestion-weighted MEFs for the North, South, and West zones are 0.561, 0.659, and 0.500 kg/kWh, respectively. In comparison, the average System-Wide MEF is 0.586 kg/kWh, which is estimated without considering congestion. These differences can be decomposed into two factors.

First, fossil fuel generators exhibit different emissions intensities in different regions, and can have different probabilities of being utilized to supply marginal demand. For instance, the higher-than-average MEFs in the South zone can be partly attributed to the higher percentages of coal-fired generations in the South, which increases the probability of coal-fired plants being used on the margin during the early mornings when demand is low.[28] In addition, natural gas generators in the West and North zones are relatively cleaner compared to those in the South.

Second, in zones with high renewable penetration, the probability of renewable energy resources (mainly wind energy in the West zone) being utilized marginally are higher. For

28. Appendix C presents the emissions intensities for all fossil fuel generators in each load zone.

instance, during early mornings and late nights with stronger wind and lower demand, wind appears on the margin for around 10% of all hours, explaining the lower MEFs in the West zone during these hours. The West zone's MEFs are 15.6% lower than the typical MEFs, with 11.4% attributable to renewable energy resources and 4.2% to relatively cleaner natural gas generators. In contrast, fossil fuel generators are responsible for the different MEFs in the north and South zones, as renewable energy resources are used marginally for less than 1% and 2% of the time, respectively.

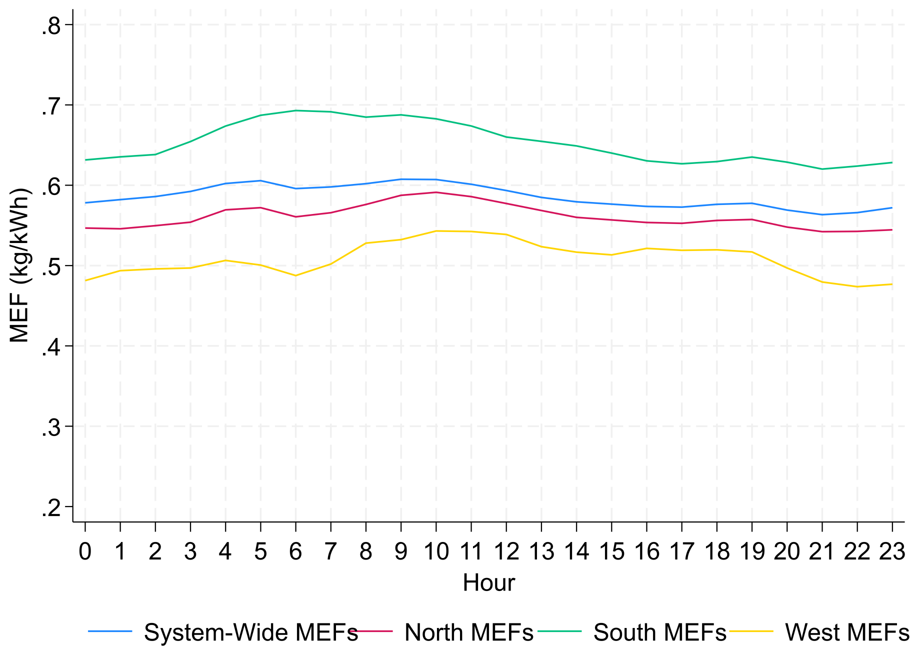

Figure 2.10: Congestion-Weighted MEFs for Each Load Zone

How do the estimated MEFs translate to the environmental values of DER technologies? Table 2.4 reports the annual carbon mitigation (kg of CO_2) of solar and batteries located in different regions of ERCOT as compared to the typical case. The results are calculated based on Equation (2.5).

As shown in Table 2.4, the environmental outcomes of a DER technology in the North

Table 2.4: Annual Carbon Mitigation of DER Technologies

	Solar	Battery Storage
Typical	-170.7	25.3
West	-147.0	22.6
South	-195.7	28.2
North	-165.0	25.2

zone do not differ substantially from using the typical MEFs. However, for a DER technology located in the renewable-rich West zone, including congestion in the estimations of MEFs can have a substantial impact. Installing a solar panel in the West zone will only achieve 86.4% of the annual CO_2 mitigation compared to the typical case. This is because the MEFs during solar generating hours are significantly lower in the West, since the West is frequently congested and the MEFs are low during congested hours. Excess solar energy will be curtailed or will increase wind curtailments in some congested hours where wind energy is used on the margin. In contrast, solar located in the South can mitigate 14.1% more carbon emissions compared to the typical case, as solar energy is used to replace dirtier fossil fuel generators in the South.

Unlike solar, the environmental values of batteries are determined by the MEFs during charging and discharging. With a carefully designed time-varying electricity rate (e.g., time-of-use rate), the battery can charge with cleaner energy and use the stored energy to displace a dirtier generation source later. Therefore, the difference in MEFs between charging and discharging or the variance of MEFs determines the potential of carbon mitigation. In the West zone, a battery can charge when the West zone is congested and wind energy is on the margin. As a result, deploying a battery in the West can often yield better environmental outcomes than in other regions. However, in our settings, deploying batteries in the West will still increase carbon emissions due to energy losses, but the increase in carbon emissions is 10. 7% less than in the typical case.

As discussed in Section 2.2, installing DER technologies can help alleviate regional congestion and indirectly impact the environment. For example, installing a battery system in the west could reduce the inflow congestion to the West zone, whereas installing a battery system elsewhere could reduce the outflow congestion in the west. However, due to limitations in our methodology, we leave this indirect environmental impact for future research.

2.8 Conclusion

Transmission congestion has become an important barrier to the growth and integration of renewable energy resources, especially wind. In jurisdictions such as Texas, where wind energy resources are located in remote areas, wind energy resources are frequently curtailed due to insufficient transmission capacity. Frequent congestion in renewable-rich regions can have a significant impact on locational MEFs, which determines the environmental values of the DER technologies.

In our paper, we analytically highlight the importance of including transmission congestion in the estimation of locational MEFs, especially for regions with high penetration of wind energy resources. In particular, we provide a novel way of estimating MEFs considering congestion using an endogenous regime switching model. When the system is uncongested, we assume that all the generation resources located in the ERCOT territory can respond to load changes. However, when a particular load zone is congested, we assume that only local generation resources will be able to respond to load changes. Compared to previous estimations using strict assumptions, our MEFs estimations can lead to more reliable estimates for environmental values of DER technologies.

Based on our MEFs, we find that installing solar in a renewable-rich regions that are frequently congested tend to have less carbon mitigation as compared to other regions. For example, a solar panel located in the West zone in ERCOT will only bring about 70% of carbon mitigation compared to the other load zones. In comparison, installing battery storage in renewable-rich region can often reduce storage-induced carbon emissions as MEFs in these regions often have greater variances. With an appropriate retail tariff designs, a battery can charge using clean energy generated from wind (which might be curtailed) when the region is congested, and discharges to replace a dirtier marginal technology when the system is uncongested.

Our results have important policy implications. Most compensation policies for DER technologies do not take into account locational effects. A solar or battery will receive the same compensation even though the underlying environmental values may vary significantly (Sexton et al., 2021). Our study highlights the importance of using location-specific subsidies based on the locational environmental values.

Our study has several main limitations. First, our study assumes assumes that DER technologies have a negligible effect on congestion. However, DER technologies can be used to alleviate congestion and could have an indirect impact on environment. Without understanding how DER technologies affect congestion, and without understanding how DER technologies and congestion affect the underlying merit order based on a dispatch model, our study do not take into consideration this indirect effect.

Second, the environmental values of DER technologies are calculated based on average MEFs. In reality, the MEFs can vary significantly in real-time. For example, MEFs can drop to zero when wind energy is used in the margin. Therefore, the variance of MEFs could be more substantial and we might underestimate the role of battery storage in carbon mitigation. We leave this to future studies when real-time marginal emissions data becomes available.

Third, due to the limitation of the regime-switching model in our study, we do not differentiate in-flow congestion with out-flow congestion. Our MEFs during congested hours is defined as a weighted-average measure for the two types of congestion. As different congestions can have different implications for the marginal emissions, future work should differentiate different types of congestion by defining multiple regimes.

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2.9 Appendices

Appendix A: Generation Mix

Figure 2.11 and 2.12 show the share of generation capacities and total generations for different technologies for each load zone in 2022. The West Zone is rich in wind energy resources, whereas the coal and natural gas generators form the backbone of the generation fleet in the North and South.

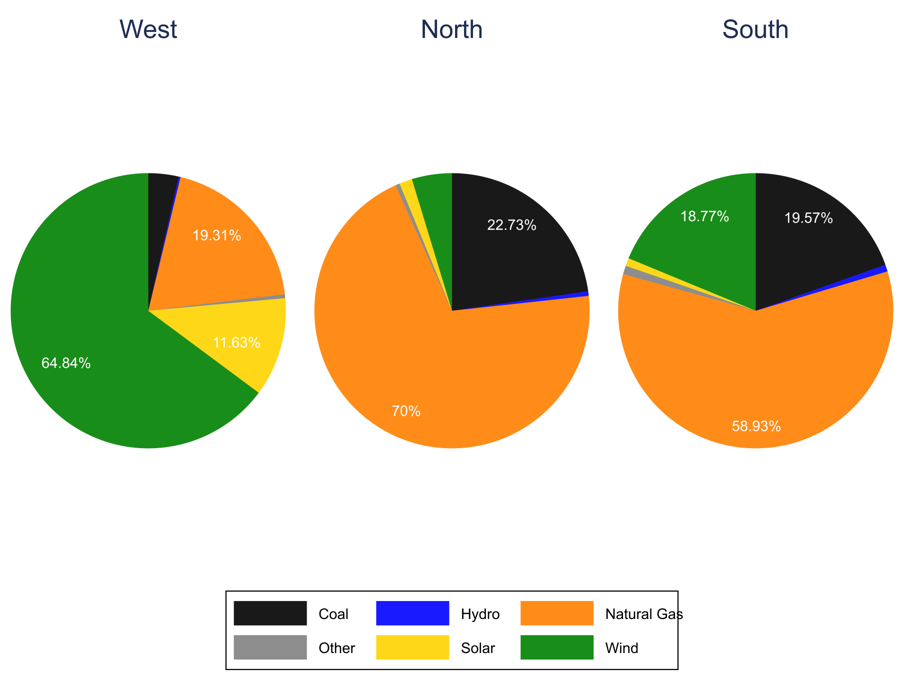

Figure 2.11: Generation Capacities (MW) by Technology

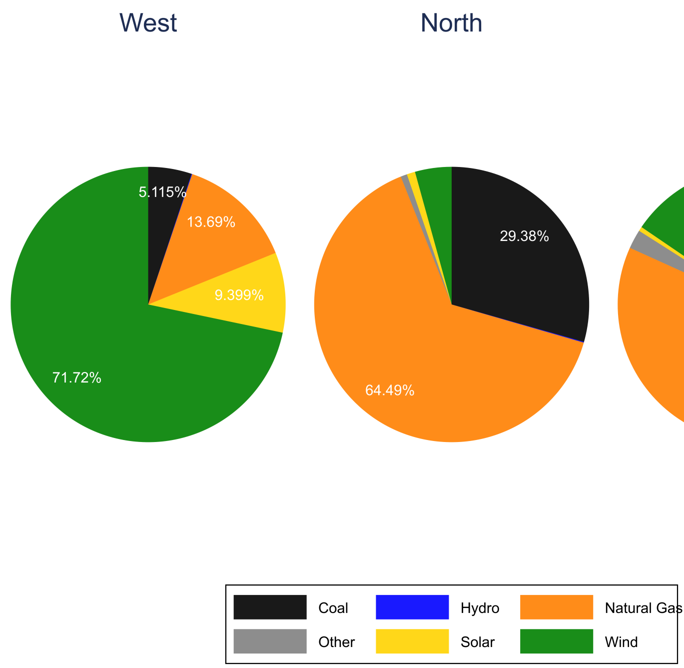

Figure 2.12: Electricity Generations (MWh) by Technology

Appendix B: Emission Intensities for Fossil Fuel Generators by Load Zone

Figures 2.13-2.15 plot the emission intensities for fossil fuel generators in the West, North, and South load zones, respectively. The emissions intensity for a plant is calculated by dividing the total annual emissions (in kg) of the plant by the total electricity generation (in kWh) in 2022. All data are from the EIA-923 form (EIA, 2023).

Compared to the North and South, the natural gas plants in the West are relatively cleaner. For an average West demand of less than 5,000 MWh, around 2,000 MWh of natural gas generation capacities have emissions intensities lower than 0.5 kg/kWh. The North and South have similar generation mixes. However, given that the South load (10,694 MW) is much lower than the North (16,123 MW), cheaper coal-fired generators are called upon more often in the South than in the North. Additionally, the average emissions intensity is slightly higher in the South, which means that, on average, a South plant is more polluting than a plant in the North.

It is worth noting that the generators are called upon based on their marginal cost (in a competitive market) rather than emissions factors. Without calculating the marginal costs for each generator unit and ranking the generators accordingly, it is difficult to assume which generators are more likely to be deployed on the margin. Due to the scope of our work, we leave this to the future.

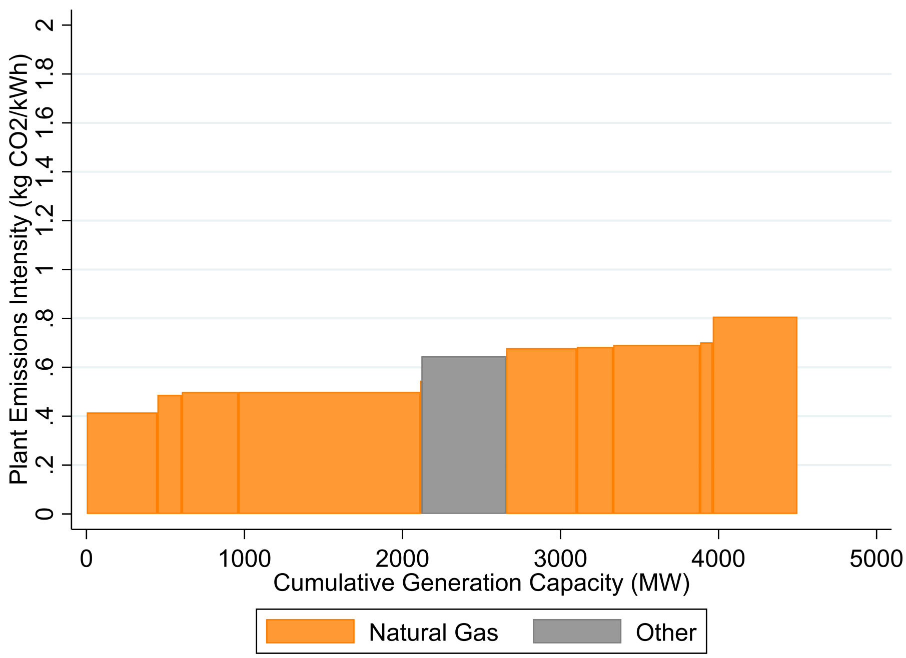

Figure 2.13: Emission Intensities for West Generators

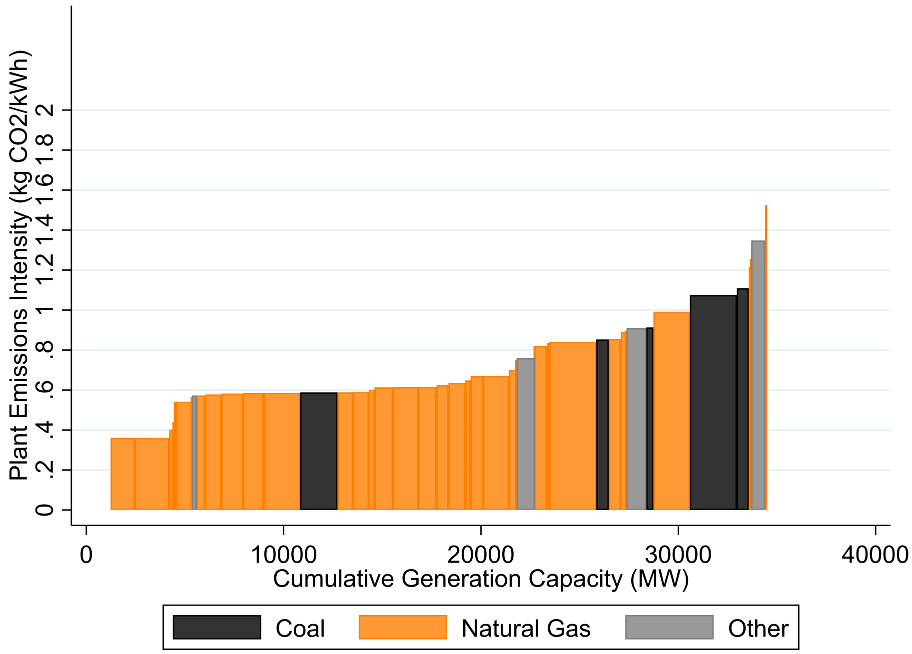

Figure 2.14: Emission Intensities for North Generators

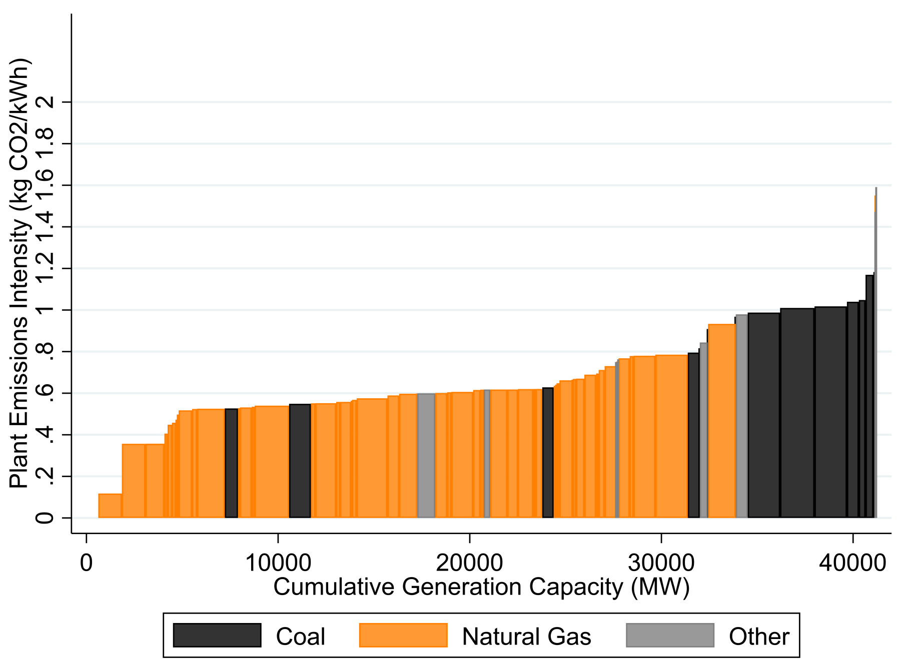

Figure 2.15: Emission Intensities for South Generators

Appendix C: Regional Average MEFs (Congested vs. Uncongested)

Table 2.5 reports the regional MEFs using the regime-switching model without hourly interactions. The regional load and ERCOT load presents the MEFs during congested and uncongested hours, respectively. The results are similar to the main results described in section 2.6.

Table 2.5: Regional Average MEFs (Congested vs. Uncongested)

	(1) North Emissions (kg)	(2) South Emissions (kg)	(3) West Emissions (kg)
Congested			
Regional Load (kWh)	0.561***	0.699***	0.445***
	(0.003)	(0.003)	(0.007)
Solar Generation (kWh)	-0.138***	-0.041***	-0.013***
	(0.004)	(0.004)	(0.002)
Wind Generation (kWh)	-3.478	-1.881***	-0.170***
	(0.026)	(0.003)	(0.001)
Unongested			
ERCOT Load (kWh)	0.603***	0.599***	0.619***
	(0.002)	(0.001)	(0.002)
Solar Generation (kWh)	-0.438***	-0.463***	-0.448***
	(0.005)	(0.003)	(0.003)
Wind Generation (kWh)	-0.468***	-0.391***	-0.431***
	(0.002)	(0.006)	(0.006)
Add Time Controls	Yes	Yes	Yes
Add Temperature Controls	Yes	Yes	Yes
Observations	52,577	52,577	41,457

Notes: This table presents the average regional MEFs estimated by the regime switching model. Columns (1) through (3) measures the regional MEFs for the North, South, and West load zone, respectively. Time controls include dummy variables for the month of the year, the hour of the day, and the day of the week. Temperature controls include one to fourth-degree polynomials of heating and cooling-degree days. Std. dev. in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D: Estimate MEFs using Nodal LMPs

MEF measures the average increase in total emissions when the total electricity demand is increased by 1 MW. Ideally, MEFs should be measured in real time for each node in an electricity grid. However, due to data limits, MEFs are often measured in an aggregate manner over times and locations. For example, an ERCOT-wide MEF will capture the average increase in emissions if ERCOT-wide demand is increased by 1 MW. Likewise, a locational (regional) MEF measure will capture the average increase in emissions if demand increases by 1 MW in a particular region, such as a load zone.

However, when congestion occurs, the estimation for MEFs becomes more complicated because the increase in emissions resulting from a 1 MW increase in demand will differ based on where that demand increase comes from. For example, if the demand increase happens in a wind-congested area, it should have a zero MEF. If the demand increase happens in an uncongested area, the MEF will be determined by the emissions intensity of the marginal units, most likely a natural gas plant. As a result, the average MEF in the West should be a weighted average of the two MEFs, weighted by the likelihood of where the next demand increase will happen. With access to nodal-level LMPs, the average MEFs can be represented as the weighted average MEFs for each LMP node, weighted by the corresponding electricity demand for each node.

Suppose in a perfect world where only two technologies can be on the margin: natural gas units, all with the same emission intensities, and renewable energy resources (wind) with zero emission intensity. At any time t, the regional MEF can be represented as:

$$MEF_t = \frac{d_{t,ng}}{D_t} MEF_{ng} + \frac{d_{t,wd}}{D_t} MEF_{wd} \tag{2.7}$$

which reflects the average increase in emissions resulting from a 1 MW increase in demand. The weight ($\frac{d_{t,ng}}{D_t}$) measures the percentage of the current load with natural gas units on the margin. For example, if 100% of the current load has natural gas units on the margin, then the current regional MEF should be equal to MEF_{ng}, which is the MEF we estimated using Equation (2.1) Note that wind could still generate electricity when this happens, as long as they are not used on the margin.

Based on Equation (2.7), the average regional MEF across time is:

$$MEF = \frac{1}{t}\sum_{t}\frac{d_{t,ng}}{D_t}MEF_{ng} \tag{2.8}$$

Note that the second term from Equation (2.7) is zero because the emissions intensity of wind is zero. Basically, Equation (2.8) states that the average regional MEF should be equal to the emission intensity of the marginal natural gas units, weighted by the likelihood that a natural gas unit is on the margin at any time t, averaged over time.

If we have nodal-level data, such as demand, renewable generation, and emissions in each node. We can estimate the MEF for each node when natural gas is on the margin (which indicates nodal-level LMP>0). The nodal-level MEF can then be calculated as:

$$MEF_i = \frac{t_{i,ng}}{t}MEF_{i,ng} + \frac{t_{i,wd}}{t}MEF_{i,wd} \tag{2.9}$$

which is the weighted average MEF based on the percentage of time when a natural gas unit is on the margin. To calculate the regional MEF, we need to consider the probability for a demand increase to occur in a node, which is implied by the demand size of that node. Formally, the MEF measures in a region can be represented as the following:

$$MEF = \sum_{i}\frac{d_i}{D}MEF_i = \sum_{i}\frac{d_i}{D}\frac{t_{i,ng}}{t}MEF_{i,ng} \tag{2.10}$$

Suppose $MEF_{i,ng}$ is the same across nodes, the regional MEF can be represented as:

$$MEF = MEF_{ng}\sum_{i}\frac{d_i}{D}\frac{t_{i,ng}}{t} \tag{2.11}$$

which provides an estimate for the average MEFs in different regions. As the environmental values of a DER technology is often based on some average MEF estimates, Equation (2.11) provides a simple way of calculating this average MEF, without accessing real-time emissions data.

Appendix E: Weather Stations Selected by the IV-LASSO Procedure

Figure 2.16 plots the locations of selected weather stations identified using the IV-LASSO procedure. If at least one variable (wind speed, wind direction, or air temperature) from a weather station is selected by IV-LASSO to predict ERCOT-wide congestion, it is shown on the map. As illustrated in Figure 2.16, the weather stations are distributed across ERCOT, highlighting the complexity of the ERCOT transmission system.

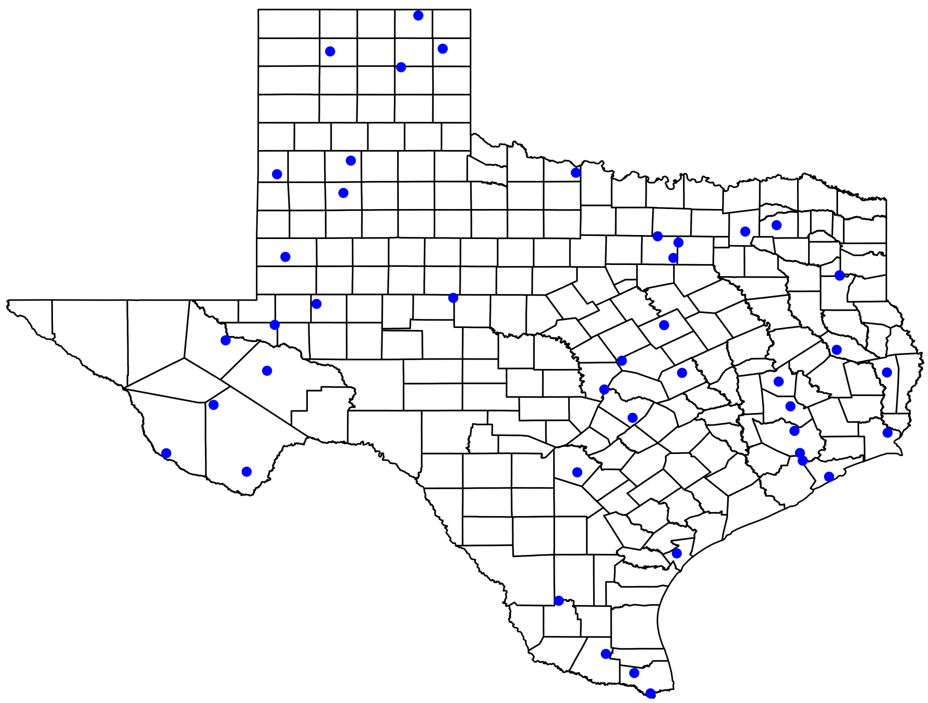

Figure 2.16: Selected Weather Stations

Appendix F: Percentage of Congested Hours by Year

Figure 2.17 plots the average time of congestion in ERCOT by year. Both transmission expansion and additional renewable generation affect congestion in any given year. In 2017,

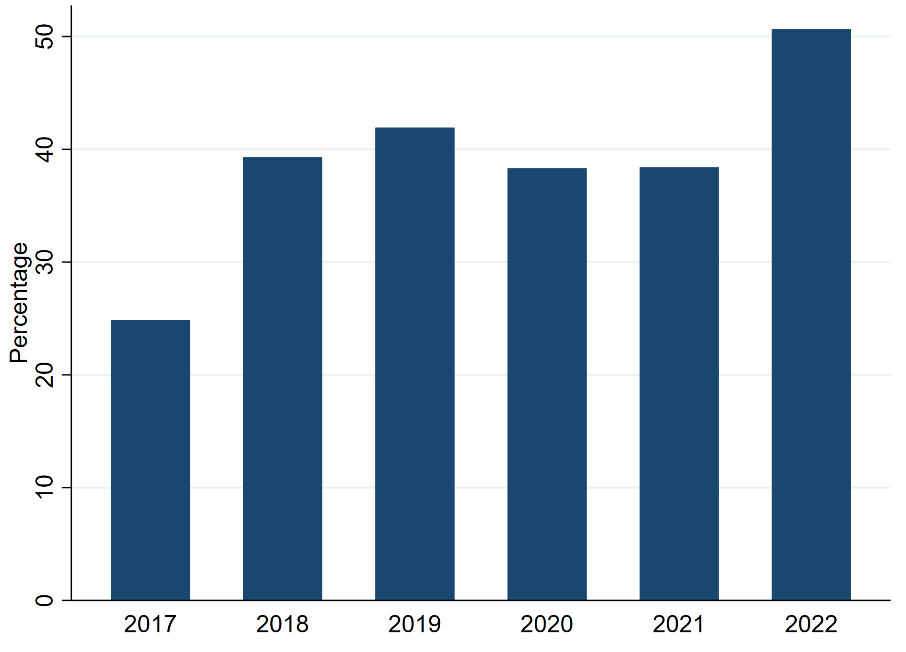

Figure 2.17: Percentage of Congested Hours by Year

the system was congested about 26% of the time. Due to increased penetration of solar and wind, the percentage of congested hours increased to around 40% between 2018 and 2021. By 2022, the percentage of congested hours was increased to more than 50%. This figure highlights the importance of considering congestion in estimating MEFs.

Chapter 3

Competing Perspectives of Maximum Demand Charges

3.1 Introduction

Economic theory suggests that the price of a good is efficient when it reflects the marginal cost of the good. However, for "natural monopolies," setting prices at marginal cost generally does not generate sufficient revenues to cover the total costs of production. As such, it is generally accepted that the regulation of these natural monopolies should aim at a second-best outcome: minimizing dead-weight loss while ensuring financial solvency (Joskow 2007). However, in reality, marginal prices in some natural monopoly industries are well above the marginal costs, leading to outcomes worse than the second-best scenario (Biggar 2009). One of the prominent examples is the electricity market, where some utilities set prices much higher than marginal costs, leading to substantial dead-weight losses (Borenstein and Bushnell 2022). This is because utilities tend to use volumetric ($ per kWh) charges to recover the fixed and variable costs for generating and delivering electricity, which distorts the marginal cost signal for electricity consumption (Wood et al. 2016).

Finding an efficient and equitable way to recover the large fixed costs faced by electric utilities is a long-standing question in the electricity sector (Borenstein 2016). In particular, the costs of maintaining a reliable grid are expected to increase in the future. The increase stems from the rising demand for expanding electric network infrastructure, driven by the increased electrification from electric vehicles and electrified heat pumps (Elmallah et al. 2022). Consequently, there is an increased urgency for more efficient tariff designs to mitigate the need for expensive network expansion. In particular, maximum demand charges (MDCs) that charge customers based on their maximum demand (in kW or kVA) over a certain period have gained significant attention from regulators and utilities. As such, whether MDCs can provide efficient and fair fixed cost recovery and whether MDCs should play a larger role in the recent evolution of tariff designs have become topics of considerable debate.

MDCs have been used for commercial and industrial customers for several decades, serving as a tool to manage maximum demand and ensure that customers who place higher demands on the grid pay their fair share of costs (Berg and Savvides 1983; Neufeld 1987). By charging MDCs, utilities are less reliant on volumetric charges to recover the fixed costs of network infrastructure, enabling them to have more efficient marginal prices. In addition, it has been argued that MDCs provide a price signal to customers to reduce the maximum demand, which can ultimately lead to a lower system maximum demand (at various levels of the grid network) and lower investment costs for additional capacities for the generation, transmission, and distribution of the electric grid (Wood et al. 2016).

Traditionally, residential customers have rarely been subjected to MDCs (Hledik 2014). However, it has been argued that MDCs could play a crucial role in accommodating increased electrification and mitigating the need for future expansion of distribution networks, similar to their use in managing system maximum demand for commercial and industrial customers (Elmallah et al. 2022).

For MDC to effectively reduce grid investment costs, customers must be sensitive to the price signal, and the timing of the price signal should coincide with the system maximum demand (Brown and Sappington 2018). In particular, since most MDCs target customer-specific maximum demand rather than system maximum demand, their effectiveness in reducing system maximum demand is frequently questioned (Brown and Sappington 2018). In addition, only a few studies have empirically examined the demand responses from MDCs, and these studies are often subject to the unique characteristics of MDC designs (e.g., Caves et al. 1984; Taylor and Schwarz 1986; 1990; Stokke et al. 2010). As a result, more evidence is needed to assess the effectiveness of MDCs in terms of maximum demand reductions.

Concern for fairness is another aspect of the ongoing debate about MDCs. As argued by Wood et al. (2016) and Hledik (2014), MDCs can better align electricity bill charges with the cost structure of the utilities so that customers who impose higher costs on the grid will pay more. However, Borenstein (2016) argues that MDCs based on a customer's individual maximum demand are not a good approximation for grid costs because a customer's individual maximum demand does not determine the overall need for grid capacity.

The concern for fairness is particularly important in the case of residential MDCs. With the rapid expansion of rooftop solar panels, many utilities have implemented residential MDCs to address the cross-subsidy concern from non-solar to solar customers, and many more are exploring the option (Faruqui et al. 2020).[1]

Although MDCs have become increasingly popular among some utilities, the overall effectiveness of such tariffs is still under debate. Motivated by this recent debate on MDCs, we conduct a comprehensive literature review on whether MDCs can achieve efficient and fair cost recovery for utilities. Although the recent debate primarily centers on residential MDCs, it is essential to consider that residential MDCs share common objectives and features with existing MDCs for commercial and industrial customers. Therefore, incorporating evidence

1. Section 3.2.2 provides a detailed analysis of this issue.

from all types of customers is crucial to providing a comprehensive understanding.

A central issue in this debate is whether MDCs can effectively motivate "peak shaving," thereby reducing maximum demand and alleviating the need for expensive grid expansions. To address this, we first review the empirical evidence related to MDC demand responses for all types of customers. Despite the growing body of research on residential MDCs, there remains a significant gap in the literature concerning the response of large commercial and industrial customers to MDCs in recent years. These customers remain the primary targets for MDCs and can provide valuable empirical insights for retail tariff designs concerning MDCs for all types of customers. To fill this gap, we conduct a detailed case study utilizing data from large commercial and industrial customers to shed light on customer responses to MDCs.

Our case study utilizes a unique meter data set for 126 large commercial and industrial customers in Lethbridge, Alberta.[2] We focus on large customers in Alberta because, unlike other jurisdictions, large commercial and industrial customers[3] account for more than 70% of the electricity demand in Alberta, and play a critical role in determining the system peak (MSA 2014; AESO 2023). The MDCs in our case study are charged daily based on the highest electricity demand in a 12-month rolling period, providing customers with a strong price signal to reduce maximum demand. Compared to residential customers, the large customers in our dataset consume significantly more energy and can achieve substantial gains from responding to price signals, making them ideal candidates for demand response.

To perform the case study, we leverage an observed 8% decrease in the MDC rate level in Lethbridge from 2017 to 2018 to investigate the customers' demand response. To understand how customers respond to the changed price signal, we use machine learning techniques to

2. Lethbridge has a 100% coverage of smart meters and mandatory MDCs for all but small residential customers.

3. Consumers are considered large if their annual electricity consumption exceeded 250 MWh. For more information, see MSA (2014).

predict counterfactual demand for each customer, assuming that the MDC rate does not change. In particular, we use a series of climate, socioeconomic, and time variables to train customer-specific prediction models using data from 2017. We then use the "trained models" to predict customers' daily maximum demand in 2018, effectively holding the MDC level unchanged. The changes in maximum demand will be captured by changes in prediction errors between 2017 and 2018 during the period when annual maximum demand is likely to occur.

Contrary to previous studies focusing on "peak reduction", we investigate whether customers would increase maximum demand when faced with a lower MDC rate. For medium-large customers, we observed a 4% increase in electricity demand (as indicated by prediction errors) from 2017 to 2018, during the days that the annual maximum demand is most likely to occur. This implies a statistically significant but moderate change in daily maximum demand from 2017 to 2018. For large customers, we find no statistically significant evidence of a response.

These findings could be attributed to a potential asymmetry in demand responses to increases versus decreases in MDC rates. When faced with increasing MDC rate, customers might make significant investments in energy conservation or demand-shifting technologies, which could become sunk costs. On the other hand, responses to decreased MDC rates might be limited to behavioral adjustments, which tend to have a smaller impact.[4] This potential asymmetry highlights the complexity of customer behavior in response to MDC rate adjustments and suggests a need for more nuanced tariff designs. Such designs could benefit from accounting for both the long-term investments driven by MDCs and the more immediate behavioral changes associated with changed MDC rates.

4. For instance, with a lower MDC rate, customers might adjust their maximum demand through changes in cooling or heating needs, which represents a behavioral change. Conversely, investments in more energy-efficient devices or technologies in response to higher MDC rates involve sunk costs and represent a long-term commitment that may not fluctuate with short-term MDC rate changes.

Our paper contributes to the literature in three ways. First, we provide a comprehensive literature review on the role and implications of MDCs, incorporating perspectives from both proponents and critics. Second, our discussion of MDCs contributes to the ongoing debate on retail tariff designs, emphasizing the evidence needed to assess whether MDCs can facilitate fair and efficient cost recovery for utilities. Third, our empirical case study adds to the existing literature on demand responses from MDCs. Specifically, our study addresses a gap in recent empirical research by focusing on large commercial and industrial customers, which complements existing studies that primarily target smaller customers.

This chapter proceeds as follows. Section 3.2 reviews the related literature on the debate of MDCs. Section 3.3 provides a review of the literature on empirical evidence for MDC responses. Section 3.4 details the background and data of our study. The empirical methodology of the case study is presented in Section 3.5. Section 3.6 presents the main results of our case study. Section 3.7 concludes.

3.2 Review of studies of MDC

The electric utility is a classic example of a "natural monopoly" as it faces large fixed costs: setting the electricity rate at the short-run marginal cost (SRMC) will not generate enough revenue to cover its total costs (Baumol and Willig 1981; Joskow and Schmalensee 1983). Utilities have employed several options to raise additional revenues, such as increasing the average volumetric charge ($ per kWh), implementing MDCs, increasing fixed charges, etc. For large customers, MDC is one of the main ways for utility cost recovery and usually represents 30% to 70% of a customer's monthly electricity bill (NREL 2022).

For smaller customers, MDCs have rarely been implemented partially due to meter technology barriers, but the rapid distribution of smart meters in recent decades has largely eliminated this barrier (Hledik 2014). As of 2015, at least 16 utilities in the US have implemented MDCs for residential customers (Hledik and Faruqui 2016). By the end of 2019, the number of active residential MDC plans increased to 68, with at least ten mandatory plans (Faruqui et al. 2020). Residential MDCs in these utilities account for 10% to 82% of electricity bills for residential customers (Hledik 2014).

Whether MDCs can provide efficient and fair fixed-cost recovery has become a topic of considerable debate in the literature.[5] This section will review the arguments of both proponents and opponents of MDCs, focusing on three distinct but related topics:

- Can MDCs reduce system peak demand?
- Can MDCs achieve cost-causation by aligning customer bill charges to costs they impose on the grid?
- What are the distributional effects of MDCs?

3.2.1 System Peak Reduction

The potential benefits of MDCs for motivating "peak reduction" and promoting a smooth consumption pattern have been recognized for decades (Henderson 1983). Berg and Savvides (1983) attributes some of the early interest in MDCs to their potential effects of deferring capacity investments in the electricity grid. For MDCs to reduce system peak demand, MDCs need to provide price signals that correlate with the system peak demand, and customers need to be price-responsive.

5. The concept of "fairness" is subject to multiple interpretations. In this chapter, we use "cost-causation" to refer to the idea that customers who impose higher costs on the grid should pay more. We use "distributional effects" to reflect the idea that low-income customers should have lower electricity bills to improve energy affordability for low-income households. These ideas reflect the basic principles of who should pay for a public good among customers (Borenstein et al. 2021).

Until recently, most MDCs were designed to target a customer's individual maximum demand, with only a small portion of MDCs targeting the system maximum demand (Hledik 2014). This customer-specific MDC design can be traced back to the early stages of electrification and was appealing at that time due to the limitations of the metering technology[6], the need for utilities to avoid grid bypass[7], and the high correlation between individual maximum demand and system maximum demand during that period (Neufeld 1987). However, this design raises concern as customer-specific maximum demand may not correlate with the system maximum demand (Neufeld 1987; Hledik 2014; Brown and Sappington 2018). In response, system peak coincident MDCs have been implemented more frequently recently for residential MDCs (Faruqui et al. 2020). However, non-coincident MDCs are still the dominant form of MDCs in recent years, especially for large commercial and industrial customers (Passey et al. 2017). According to Passey et al. (2017), some utilities are hesitant to replace non-coincident MDCs with system peak coincident MDCs due to concerns that some customers may not be aware of the system peak or may not fully understand the term "coincident", potentially leading to unpleasant bill shock for these customers.

Existing studies have found that customer-specific MDCs are inefficient in reducing system maximum demand, even if customers are price-responsive. In particular, large industrial customers that are most likely to face MDCs tend to have the least coincident individual maximum demand (Neufeld 1987). For example, only 8% of customer-specific maximum demand reduction for industrial customers can be transformed into system peak reduction as the individual maximum demand does not usually coincide with the system maximum demand (Henderson 1983).[8]

6. The early meters (around 1910) can only record aggregate consumption and maximum consumption, but cannot record when maximum consumption occurs (Neufeld 1987).

7. A major concern for utilities at the early stages of electrification is that some large customers choose to generate electricity as an isolated plant and bypass the grid (Neufeld 1987). The costs of a customer to set up its own isolated plant are closely related to its maximum demand. Therefore, charging customers based on their individual maximum demand provides a way for utilities to exercise price discrimination (Neufeld 1987).

8. See Appendix E for a detailed discussion on how customer-specific maximum demand in our sample

Whether customers respond to the MDC signals is crucial for peak reduction, even if the price signal is correlated with the system's maximum demand. Previous studies have found significant responses from both industrial, commercial, and residential customers toward MDCs. A more detailed review of these studies will be provided in Section 3.3.

In an environment with increasing penetration of solar panels and battery storage technologies, how MDCs can be used to reduce system maximum demand and achieve bill savings utilizing these new technologies has become increasingly important. A number of studies have investigated the role of solar and batteries in reducing maximum demand and MDCs for customers. Darghouth et al. (2017) investigated the effectiveness of the use of solar panels to reduce residential MDCs. They found that solar panels are generally inefficient in reducing MDCs for residential customers because their maximum demand period typically occurs in the evenings when solar cannot generate much power. Solar panels are more effective at reducing MDCs if the MDCs are based on the system maximum demand that correlates with the solar generating hours. However, with increasing penetration of rooftop solar, the system's maximum demand is likely to be shifted away from the solar generating hours in the near future.[9]

Compared to solar, batteries are more effective in reducing MDCs. McLaren et al. (2017) found that reducing MDCs is the main driver of battery installation, and the potential of bill savings brought about by batteries under MDCs is substantial. Boampong and Brown (2020) investigated the impact of MDCs on battery operation decisions and how they affect the utilities' avoided energy and capacity costs. They found that while batteries can reduce utilities' avoided costs under MDCs, MDCs based on the system's maximum demand can induce much higher cost reduction than non-coincident MDCs.

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correlate with the system maximum demand in Alberta. Because more than 80% of the system demand is from large industrial and commercial customers in Alberta, the correlation between the customer-specific load and the system load can be higher in our sample.

9. This has already happened in regions with high solar penetration, as represented by the classic "duck curve" in California and other jurisdictions.

Other retail tariff designs have been used to reduce the system's maximum demand. Examples include time-of-use (TOU) pricing, where electricity rates change according to peak/off-peak periods; real-time pricing (RTP), where electricity rates change in real time based on wholesale electricity prices; and critical peak pricing (CPP), where electricity prices are higher during a small number of critical days or hours (Faruqui et al. 2009). When smart meter technologies that can record energy consumption in real time are not available, TOU rates have often been discussed as an alternative to MDCs (e.g., Seeto 1997; Woo et al. 2002). A potential benefit of MDCs over TOU is that they provide incentives to reduce needle peaks, where the electricity demand surges in a short period (Seeto 1997). With better meters available, it has been shown that RTP and CPP bundled with demand charges have been shown to be more effective than TOU in terms of peak reduction (Faruqui and George 2005; Faruqui et al. 2009). For example, in several pilot studies conducted among residential customers, CPP induces an average of 13-20% of system peak reduction, RTP induces an average system peak reduction of 10-14%, whereas TOU only achieves 3-6% of the system peak reduction (Faruqui et al. 2009; Faruqui and Sergici 2010; Dutta and Mitra 2017). However, these studies have not isolated the unique impact of MDCs from CPP and RTP on peak demand reduction.

In recent years, the surge in residential electrification, driven by the adoption of electric vehicles (EVs) and electric heat pumps, has drawn significant attention to the need to upgrade local distribution networks (Elmallah et al. 2022). Several studies have looked at the role of MDCs in reducing the maximum demand associated with the distribution networks (reducing local distribution peaks). For example, Abdelmotteleb et al. (2018) proposes to use a peak-coincident MDC to recover part of the distribution charges during critical peak hours of the distribution network. Turk et al. (n.d.) proposes a subscription charges based on a customer's ex-ante maximum demand subscription to recover part of the distribution charges. These studies aimed to provide incentives for customers to reduce maximum demand with respect to local distribution network, therefore, reducing the need to upgrade the distribution network.

Recognizing this potential benefit of MDCs in reducing peak demand, the effectiveness of different MDC designs is an important empirical question. For example, how would different types of customers (residential, commercial, and industrial) respond to system peak coincident MDCs compared to non-coincident MDCs? Is there any evidence to support the claims that customers would not fully comprehend the term “coincident” when designing MDCs? How efficient are system peak coincident MDCs compared to non-coincident MDCs at reducing system total avoided costs? How efficient are MDCs based on the monthly maximum demand compared to MDCs based on annual maximum demand? Due to the heterogeneity and complexity of MDC designs, more studies and evidence are needed to quantify the economic outcomes associated with each MDC design.

How the MDC rate should be determined is another important question to consider when designing efficient MDCs. Currently, there is no general rule on how MDC rates are determined. In some jurisdictions, MDCs are used to recover the full or a portion of fixed distribution and transmission charges (Brown et al. 2015). However, for the efficient pricing of maximum demand reduction, the system peak coincident MDC rate should reflect the total avoided costs of system maximum demand. More broadly, the non-coincident MDC rate for a customer should reflect the system’s long-run marginal costs for serving this customer.[10] Quantifying the inefficiencies associated with different MDC rate levels in different jurisdictions can be another important empirical question to answer in the future.[11]

The most recent empirical studies on MDCs focus on residential customers (e.g., Stokke et al. 2010; Bartusch et al. 2011; Bartusch and Alvehag 2014; Öhrlund et al. 2019). However,

10. It is worth noting that the primary efficiency goal of MDC in some jurisdictions is to motivate the efficient use of the distribution network (Passey et al. 2017). For this purpose, the MDC rate should be set at the long-run marginal cost (LRMC) of the distribution network (Brown et al. 2015). More details will be provided in Section 3.2.2.

11. For example, one aspect to consider is how the price signal provided by the MDC could distort the price signals provided by other time-varying tariff designs such as RTP.

large commercial and industrial customers continue to be the main targets of MDCs and offer great potential for demand response. The last empirical study on MDCs for these large customers was conducted 40 years ago. Therefore, new studies are needed to account for advancements in empirical methodologies, potential changes in customer preferences and behaviors, and the evolution of underlying technologies installed at end-user facilities. In addition, recent developments in metering technologies, especially high-frequency data from smart meters, have enabled more advanced methods to be used to investigate the demand response towards MDCs. Considering the importance of large customers in terms of demand response and their relatively outdated designs of customer-specific MDCs, future studies should evaluate the role of MDCs and the demand response of large consumers to MDCs.

3.2.2 Cost-Causation

Proponents argue that MDCs provide better alignment of electricity tariffs and utility network costs. This can lead to better price signals for efficient use of the electric network (Hledik 2014; Passey et al. 2017; Brown et al. 2015). The reason is that network costs are often closely related to maximum demand at various levels. For example, a customer's distribution service cost is determined in part by the maximum demand of this customer; a neighborhood's need for an electricity distribution substation is determined by the collective maximum demand of the neighborhood; and the need for additional generation capacity is determined by the maximum demand of the system (Hledik 2014). Therefore, MDCs can reasonably approximate the fixed costs a customer imposes on the grid.

However, as argued by Borenstein (2016), a customer's individual maximum demand can only capture a portion of the costs associated with the grid's need for generation, transmission, and distribution capacity because the individual maximum demand may not coincide with the system maximum demand. In addition, the customer-specific distribution service costs are largely made up of sunk investment costs determined up-front by the attributes of the distribution service instead of the maximum demand of the customer (Borenstein 2016).[12] Economic theory suggests that the distribution tariff should provide price signals based on its long-run marginal costs[13] and recovering sunk costs with MDCs will distort this price signal (Brown et al. 2015). Therefore, it is more efficient to recover these sunk costs with fixed charges based on the customer's service capacity (Borenstein 2016). However, as argued by Passey et al. (2017), customers belonging to the same customer class (i.e., residential) tend to have distribution services with the same technical attribute. Allocating sunk costs equally to all customers within a customer class can lead to distributional concerns, as low-income customers would have to pay the same as high-income customers. More discussion on distributional effects is available in Section 3.2.3.

Empirical evidence on how cost-reflective the MDCs are is scarce in the literature. To the best of our knowledge, Passey et al. (2017) is the only study examining how a customer's MDCs reflect the long-run marginal cost of providing network service to this specific customer. Passey et al. (2017) use a customer's contribution towards the highest system demand in a year to proxy the long-run marginal cost of serving this customer. Based on a sample of over 2,000 Australian households and a local MDC tariff, they found that non-coincident MDCs have a low correlation coefficient ($r = 0.56$) with the long-run marginal cost. In comparison, a system peak-coincident MDC with a similar design can raise the correlation coefficient to 0.9.

While the study of Passey et al. (2017) provides insight on how MDCs correlate with long-term marginal costs, its long-run marginal cost measure only captures part of the costs that correlate with the system peak. Given the complexity of the energy grid, the long-run

12. According to Hanser (2013), about 80% of the distribution service costs are sunk investment costs. However, due to increased electrification (e.g., electric vehicles, electric heat pump), this is expected to change in the near future.

13. Long-run marginal costs refer to the investment expenses needed to meet a marginal increase in the maximum capacity of an electric network.

marginal cost will also be affected by the customer's location on the electric network (Brown et al. 2015). Future studies should investigate the locational cost-causation of the MDCs. In addition, the correlation analysis of Passey et al. (2017) does not capture how the price signals provided by the MDCs reflect the level of long-run marginal costs. Achieving economic efficiency requires setting the MDC rate at the long-run marginal cost (Brown et al. 2015). However, MDCs from the real world usually deviate from the long-run marginal costs,[14] and future studies should quantify the inefficiencies associated with this price distortion.

3.2.3 Distributional Effects

The distributional effects of tariff designs are a crucial factor that can impede retail rate reform for residential customers (Joskow and Wolfram 2012). In the US, over 80% of utility requests to increase fixed charges are denied by regulators over concerns about the potential distributional effects on low-income customers (Trabish 2018). For residential customers, fixed charges only account for a small portion of their electricity bills, whereas volumetric charges typically account for over 90% (Hledik 2014). Under this tariff structure, customers who use less electricity will face substantially lower electricity bills than customers who use electricity extensively. If a utility uses fixed charges to recover fixed costs, the electricity bills of small customers will increase substantially (Hledik and Faruqui 2016). However, with MDCs, this redistribution effect between small and large customers is much smaller, as smaller customers with a lower maximum demand are not automatically worse off (Hledik 2014; Wood et al. 2016). As evidence suggests that low-income customers tend to be low-usage customers[15], have a flatter consumption pattern[16], and have higher demand response

14. Utilities tend to recover network costs through volumetric charges, especially for residential customers, due to distributional effects concern (Brown et al. 2015). Even if residential customers face MDCs, the MDC rate tends to be low (Brown et al. 2015). For large industrial and commercial customers, the MDC rate can also deviate from the long-run marginal costs as MDCs can be used to recover some of the sunk costs.

15. For example, see Bird et al. (2015), Lazar (2016), Wood et al. (2016), and Zethmayr and Makhija (2019).

16. For example, see Lazar (2016) and Zethmayr and Makhija (2019).

than high-income customers[17], MDCs are often favored by utilities and regulators concerned with social fairness (Wood et al. 2016).

However, when better energy conservation and self-generating technologies become more accessible, smaller customers (who purchase fewer kWh from the utilities) may not imply low-income customers (Hledik 2014). In particular, energy efficiency devices and solar panels are more affordable for high-income customers, which reduces the need to purchase electricity directly from the utilities. In addition, some low-income customers can have a limited ability to shift load (Wood et al. 2016). To address these concerns, a few studies use both billing and income data to simulate the distributional effects of various tariff designs. In particular, Hledik (2014) simulated the effects of MDCs on customer electricity bills compared to a tariff design with high fixed charges. He finds that low-income customers are more likely to benefit than the average customer under MDCs. In particular, around 75% of low-income customers are better off under the MDCs compared with fixed charges. To quantify the distributional effects of MDCs compared to the current two-part tariff design (small fixed charges plus significant volumetric charges), Hledik and Greenstein (2016) collected a sample of over 2,000 residential customers in Vermont, US. They find that, unlike fixed charges, MDCs do not disproportionately affect low-income customers, and the regressive distributional effects of MDCs can be minimized by developing a careful transition strategy, including education, optional rate exemptions, or other social programs.

Reducing cross-subsidy concerns among customers, especially residential customers, is another significant benefit proposed by the proponents of MDCs (Hledik 2014). In particular, in an environment with rapid expansion of rooftop solar panels, there is a significant cross-subsidy concern between solar and non-solar customers (Brown and Sappington 2018). This is because most utilities rely on volumetric (per kWh) charges to recover fixed costs, so the per kWh volumetric rate is often higher than the avoided energy costs for the utilities.

17. For example, see Wolak (2010), Gyamfi et al. (2013), and Burger et al. (2020).

As solar customers can self-generate part of the electricity and do not purchase from the utility, the lost revenues outweigh the avoided costs, forcing utilities to raise the volumetric rate for all customers. In addition, solar customers are often allowed to export excess power generated from solar panels back to the grid and be compensated at the prevailing volumetric rate. This further pressured utilities' financial solvency, forcing them to increase volumetric charges. To eliminate this cross-subsidy concern, the electricity tariff should be aligned with the cost structure of the utilities: the volumetric charge should reflect the avoided energy costs, and fixed charges should be recovered through alternative tariff designs, such as fixed charges or MDCs. Hledik (2014) argued that recovering fixed costs through fixed charges can raise distributional concerns, whereas MDCs help protect small customers and provide opportunities for customers to reduce electricity bills.

However, as advocated by Borenstein et al. (2021), an income-based fixed charge can address the distributional concern of higher fixed charges for low-income families. Income-based fixed charges would assign different levels of fixed charges based on households' ability to pay. By setting the volumetric rate at the SRMC and recovering fixed costs through income-based fixed charges, utilities can achieve both efficiency and equity. Furthermore, a utility can design income-based fixed charges in a way that ensures that low-income households do not suffer, therefore ensuring a progressive distribution among households (Borenstein et al. 2021).

Current studies that look at the distributional effects of MDCs generally compare between MDCs and non-income-based fixed charges or between MDCs and volumetric charges.[18] How income-based fixed charges should be designed and what the distributional effect it has compared to MDCs have not been empirically examined in the literature. Future studies are needed to answer these questions.

18. For example, see Hledik (2014), Rubin (2015), Hledik and Greenstein (2016), and Lazar (2016).

3.3 Review of Empirical Studies on MDC Response

In theory, MDCs provide incentives for customers to reduce peak demand in order to cut electricity bills (Taylor and Schwarz 1986). In some utilities, MDCs represent up to 80% of a customer's monthly electricity bill (Hledik 2014). But to what level are customers willing to exploit the opportunity? As summarized in Table 3.1, only a handful of studies have attempted to answer this question.

Early empirical studies (e.g., Henderson 1983; Mountain and Hsiao 1986) tend to focus on large commercial and industrial consumers as they are the primary targets of MDCs. Henderson (1983) estimates the MDC elasticity of peak demand using load data at the utility level. Using cross-sectional data from 89 privately owned utilities, Henderson (1983) estimated that the MDC elasticity is -0.78 and -0.61 for industrial and commercial loads, respectively. Mountain and Hsiao (1986) and Veal (1986) conducted an analysis based on large industrial firms in Ontario, Canada. Mountain and Hsiao (1986) measure the substitution between monthly maximum demand and off-peak demand in response to changes in price structure (demand charge and energy charge). They find that about half of the firms in their sample show significant responses toward MDCs by reducing maximum demand. Veal (1986) uses the extreme value likelihood function to estimate how the maximum demand of industrial firms changes with different levels of MDC and find a small MDC response for 3 of 5 cement firms.

Caves et al. (1984) and Taylor and Schwarz (1986) are the first to measure demand response for residential customers. They conducted experiments by randomly assigning households to a time-of-use (TOU)[19] plus demand charge group and a flat rate control group. They find positive evidence for peak reduction under the MDCs. In addition, both Caves

19. Under a TOU rate, a customer will pay according to the time of day and day of the week he uses electricity.

Table 3.1: Review of Empirical Studies of Demand Charge Response

Studies	Regions	Type[a]	Period	Data		Response
				Structure	Level	
Henderson (1983)	US	C&I	1970	Cross-sectional	Utility	Significant
Caves et al. (1984)	Wisconsin (US)	R	1977-1979	Panel	Household	Significant
Mountain and Hsiao (1986)	Ontario (Canada)	I	1970-1980	Time-series	Firm	Some Significant
Veal (1986)	Ontario (Canada)	I	1970-1977	Time-series	Firm	Some Significant
Taylor and Schwarz (1986)	North Carolina (US)	R	1978-1983	Panel	Household	Significant
Taylor and Schwarz (1990)	North Carolina (US)	R	1985-1988	Panel	Household	Significant
Stokke et al. (2010)	Norway	R	2006	Panel	Household	Significant
Bartusch et al. (2011)	Sweden	R	2005-2008	Panel	Household	
Bartusch and Alvehag (2014)	Sweden	R	2006-2012	Panel	Household	
Öhrlund et al. (2019)	Sweden	C&R	2015-2017	Panel	Consumer	Significant

[a] C, I, and R stand for commercial, industrial, and residential customers, respectively.

et al. (1984) and Taylor and Schwarz (1986) found that customers had a higher tendency to shift maximum demand (highest demand in a month) to off-peak periods compared to peak periods.

Taylor and Schwarz (1990) conducted a follow-up study and estimated the long-run effects of TOU rates with demand charges. They find that MDCs reduce both maximum demand and demand in peak periods. Moreover, they found a surprising result: MDCs induce a greater reduction in demand in peak periods than in the maximum demand itself. This highlights the possibility that customers are not aware when their demand peaks, especially when smart meters are not accessible. In addition, they find that the customer response towards MDCs is increasing over time.

These studies with controlled experimental designs provide valuable insight into customer response towards MDCs, but they were conducted more than 30 years ago. Therefore, the results do not account for changes in consumer behavior caused by shifts in preferences, changes in business electric equipment or household appliances, and changes in economic conditions (Hledik 2014). For instance, customers from the early studies did not have smart meters, which means that customers did not know their current electricity usage or when their demand peaked. This could explain why customers tend to shift both the maximum and peak periods demand to off-peak periods.

Compared to previous studies (e.g., Caves et al. 1984; Taylor and Schwarz 1986; 1990), more recent studies often lack an experimental design and therefore must rely on econometric techniques to infer causality. Stokke et al. (2010) analyzed the demand response of 443 Norwegian households to a winter-only demand charge in 2006. They estimate a fixed-effects panel model based on hourly meter data. They use hourly dummy variables to capture the changes in hourly energy demand when MDCs are active, and control for factors like temperature, wind speed, and daylight hours. They find that there is an average 5%

reduction in maximum demand due to MDCs, corresponding to a 0.7% reduction in total load.

Bartusch et al. (2011) and Bartusch and Alvehag (2014) use descriptive analysis to study the effects of demand charges on 500 households in Sweden. Based on a descriptive comparison of households before and after the introduction of the MDCs, they found that single-house consumers (residential consumers who live in a single house) had reduced maximum demand in response to the MDCs by 10% to 22% during the summer. However, during winter months, the maximum demand change exhibits much higher variations, from a 3% increase to a 22% decrease. In addition, they found that single-house consumers had shifted consumption from peak to off-peak hours by about 2.5% during the summer, but only 0.25% during the winter. However, due to its descriptive nature, it is difficult to establish a causal relationship between the introduction of MDCs and the reduction in electricity maximum demand.

Öhrlund et al. (2019) conducted the most sophisticated and recent study on MDC responses using billing data for around 50,000 small customers (but only 612 with MDCs). He used a propensity score method to create a sample of 1,110 customers with an MDC and a control group. Using a customer-specific two-level time series model, Öhrlund et al. (2019) found that the MDC group has lowered maximum demand by 7.4% compared with the control group since the MDCs were introduced. However, Öhrlund et al. (2019) did not find evidence that customers with stronger financial incentives and can benefit more from demand response (higher potential bill savings) will respond more to the MDCs. This finding suggests that customers could respond to price signals for non-financial reasons (Öhrlund et al. 2019). The MDC treatment in Öhrlund et al. (2019) is limited to a particular region in Sweden. While this feature allows Öhrlund et al. (2019) to define a control group using regions proximate to the treatment region, it may prove challenging to replicate this approach in other jurisdictions.

It is worth noting that there are no studies to the best of my knowledge that investigate large commercial and industrial customers' responses to MDC since the late 1980s. Considering that large customers possess great potential for demand responses and continue to be the main recipients of MDCs, it is vital to provide an updated study on how they will respond to MDCs. Our study aims to fill this gap.

In addition, unlike previous studies, our study looks at how customers would respond to changes in the level of MDCs, rather than to the existence of MDC. Therefore, our study provides insight into how financial incentives of MDCs, rather than the perceptions of MDC itself, can affect customer decisions. Previous studies have claimed that the mere presence of the MDC can induce demand response due to non-financial reasons such as social responsibilities (Darby and McKenna 2012). In addition, there is limited evidence suggesting that customers will respond to the financial incentives provided by MDCs (Öhrlund et al. 2019). Our study aimed to provide direct evidence on how customers will respond to the financial incentives provided by the MDC.

Similarly to the study of Stokke et al. (2010), our study relies on pre-treatment vs. post-treatment comparisons to estimate customer demand response toward MDCs. However, our data and methodology differ from Stokke et al. (2010) in two ways. First, Stokke et al. (2010) examines the data for only one year, with the pre-treatment period occurring during summer and the post-treatment period during winter. The unique environmental conditions in Norway can lead to significantly different consumption patterns between seasons, which could be difficult to control using a fixed-effects model. In comparison, the pre-treatment vs. post-treatment comparison of our study occurs within the same season, and our model accounts for other factors, including temperature and economic conditions. Second, by using a machine learning method to create a counterfactual demand profile for each customer, our study can better account for heterogeneity across customers and can provide more robust results than a fixed effects model.

3.4 Background and Data of the Case Study

The previous section summarizes the primary motives of MDCs in three main aspects. As mentioned, a crucial motivation for MDCs is to incentivize maximum demand reductions, thereby reducing electric grid upgrade costs.[20] The remainder of the study will focus on this aspect by providing an empirical analysis that fills an important gap in the literature.

3.4.1 Case Study Objective

As summarized in Section 3.3, previous studies have generally found that MDCs can reduce maximum demand. However, recent studies have focused mainly on residential and small commercial customers. The main objective of our case study is to provide an updated examination of demand response from large commercial and industrial customers. Estimating demand response from large customers is interesting for three reasons. First, large commercial and industrial customers have been the primary targets of MDCs for decades, and MDCs continue to be an important feature in electricity charges faced by large customers (Hledik and Faruqui 2016). In particular, it is estimated that almost all medium and large customers are subject to MDCs or have the option to select electricity plans with an MDC feature (McLaren et al. 2017).

Second, commercial and industrial customers, compared to residential customers, present greater potentials for demand response in the electric grid. In general, large customers can derive greater benefits from responding to MDCs and tend to have better means to adjust their demand. For instance, large customers are more likely to have smart meters and may install battery technologies, employing battery operation algorithms to mitigate MDCs (McLaren et al. 2017). Therefore, large commercial and industrial customers could be more

20. Although how customer-specific electricity demand correlates with the system demand is not the main objective of this paper, we provide a detailed summary in Appendix E.

price responsive toward MDCs than residential customers. Given that large customers can play an important role in terms of maximum demand reduction, it is crucial to estimate the demand response for these customers and design more effective MDCs accordingly.

Third, estimating demand response from large customers can offer insight into the maximum response to demand from smaller customers. For example, if large customers demonstrate limited demand response, it is reasonable to assume that residential customers will also exhibit limited demand response, considering that larger customers have greater incentives to respond.[21] In addition, conducting pilot MDC studies for residential customers can be costly or infeasible in some jurisdictions. In such cases, estimating the demand response for large customers can be more feasible as the data is readily available. In summary, considering the significance of large customers in the context of MDCs and the scarcity of related studies in recent years, it is crucial to estimate the demand response for these customers. Our study aims to fill this gap.

Apart from the goal of estimating demand response toward MDCs from large customers, our study differs from previous studies in two unique ways. First, while previous studies have focused on the existence of MDCs, our case study examines changes in the level of MDCs. Notably, previous studies have emphasized the significance of the mere presence of MDCs in terms of demand response, attributing it to non-financial factors. For example, Öhrlund et al. (2019) observed that customers' demand response does not consistently grow in alignment with the magnitude of their financial incentive. Therefore, Öhrlund et al. (2019) concluded that demand response can be partially attributed to non-financial factors such as social responsibilities. Given that MDCs already exist in our study and assuming that rate changes solely affect the financial incentives of customers, our study can isolate the impact

21. Large customers are likely to respond more to demand charges than smaller customers due to several factors. They may benefit from economies of scale when implementing energy management solutions like batteries, automation, and solar systems. In addition, large customers might have more financial incentives and resources to invest in such technologies, potentially enhancing their ability to manage demand charges.

of financial incentives from other factors. As such, our study aims to investigate whether demand response to MDCs will be influenced by the financial incentives provided by the MDC rate rather than simply by the presence of MDCs.

Second, our study looks at the implications of a reduction in MDC rates, a perspective not explored in the existing literature. Our study aims to understand whether customers will increase maximum demand when the MDC rate is reduced, while conventional studies have often focused on the opposite scenario. Our study offers valuable insight into customer behavior and the effectiveness of MDCs in influencing customer maximum demand. In particular, understanding how customers react to a decrease in MDC rates is essential for policymakers and utility companies in devising strategies for demand management and cost recovery.

To perform the case study, we utilize a MDC rate change for large customers located in Lethbridge, Canada. The remaining sections of the case study are organized as follows. Section 3.4.2 discusses the background information for the MDCs in Lethbridge. Section 3.4.3 outlines the data used in our case study. Section 3.4.4 summarizes the impact of the MDC rate change on customers' electricity bills. Section 3.5 presents the empirical methodology employed for the case study. Section 3.6 presents the main results. Section 3.7 concludes.

3.4.2 Distribution Tariffs in Lethbridge

Lethbridge is located in southern Alberta, Canada, with a total population of 87,572 in 2016 (Statistics Canada Government of Canada 2023). Agriculture is the primary industry in Lethbridge, and the city holds more than 120 agri-food processing companies (Choose Lethbridge 2020). Lethbridge has a moderate continental climate. A normal summer in Lethbridge has an average temperature between 8°C (46.4 °F) to 26°C (78.8 °F) whereas a normal winter has an average temperature between -11°C (12.2 °F) to 3°C (37.4 °F).

Retail electricity prices in Lethbridge are composed of three parts: energy charges, transmission charges, and distribution charges. MDCs are utilized in Lethbridge to recover the distribution and transmission charges associated with delivering electricity. In Alberta, there is a restructured wholesale market for energy rates, whereas the transmission and distribution charges are set under a regulatory process. In Lethbridge, distribution tariffs are approved by the Alberta Utilities Commission (AUC) and the City of Lethbridge under the cost-of-service regulation (Alberta Utilities Commission 2021; City of Lethbridge 2023). The rates are designed to ensure that the revenues earned by the utility cover its operating costs and provide a reasonable rate of return to its investors.

The City of Lethbridge owns and operates a Municipal Electric Distribution Utility, which is responsible for providing access to the municipal distribution system and the provincial transmission grid. On the 1st day of January each year, the City of Lethbridge establishes a new Distribution Tariff Bylaw, which sets transmission and distribution charges for different rate classes.

MDCs are mandatory for all medium and large customers in Lethbridge, constituting most commercial and industrial customers, and some large residential customers. The same rate applies to the same rate class regardless of retailer affiliation (which only affects energy charges). Unlike many MDCs that are based on the monthly maximum demand, MDCs in Lethbridge are calculated based on the maximum demand over the past 12 months[22] (City of Lethbridge 2023). Compared to previous studies (where MDCs are based on the monthly highest maximum demand), MDCs in Lethbridge provide a strong incentive for customers to reduce annual maximum demand rather than monthly maximum demand. The incentive can

22. The MDCs in Lethbridge is called the "ratchet demand". Customers will pay their demand fees according to the highest metered demand on their services over the past year. If a customer's current monthly demand reading is lower than readings in the past 11 months, then the highest demand in those 11 months is used to calculate the current bill. If the current monthly demand reading is higher than readings in the past 11 months, then the current demand becomes the billing demand and the new ratchet value moving forward in time.

exhibit significant seasonal effects based on the characteristics of a customer (e.g., winter-peak vs. summer-peak). On top of these charges, distribution utilities often use rate riders to adjust their revenues if the approved revenues do not match the actual operational costs.

3.4.3 Data

Our study makes use of meter data for 126 large commercial and industrial customers in Lethbridge, which represents the entire population of customers of rate codes 995 and 996 (43 995 customers and 83 996 customers, respectively).[23] The characteristics of the customers, such as industry and retailer affiliation[24], are not available from the dataset. This data set provides 15-minute energy usage (kWh) and energy demand (kVA) measures between May 2017 and March 2019 for each customer. On average, a 996 customer uses 222 MWh of electricity per month, about the monthly consumption of a 50,000 sqft grocery store, a public high school, or a hotel (Energy Information Administration 2018). An average 995 customer uses 106 MWh of electricity per month, about the monthly consumption of a 25,000 sqft grocery store. More information on customer electricity consumption characteristics is provided in Section 3.3.3.

In addition to meter data, we also collect data on wholesale electricity rates, weather information, monthly unemployment rate, and future prices of oil and natural gas to control for factors that affect consumption decisions. In Alberta, most industrial and large commercial customers act as self-retailers who purchase power directly from the wholesale electricity market (Alberta Utilities Commission 2021).[25] The electricity rates they pay will

23. This rate class contains customers with a maximum energy demand of 150 kVA or higher. Like kW (kilowatts), kVA is used to measure instantaneous energy demand but without considering the energy conversion efficiency of the system. kVA is a measure of apparent power, which is the total amount of power used in a system. kW is a measure of actual power, or the amount of power that is converted for actual use. In a 100% efficient system, $kW = kVA$. In general, 1 kVA$\approx$ 0.8 kW and 1 kWh is using 1 kW of power continuously for an hour. A detailed description of the rate classes is available in Appendix A.

24. This includes self-retailer, who can purchase electricity directly from the wholesale market.

25. Like many other restructured electricity markets, Alberta's wholesale electricity price (also known as

be the wholesale electricity price plus an energy market trading charge (fixed per MWh). We therefore use the monthly average wholesale electricity price to proxy the energy rate they face. However, as the energy demand of large customers can endogenously affect the wholesale electricity price, we use natural gas future price as an instrumental variable for the wholesale rate. Natural gas future price is an ideal instrument because it can affect the wholesale electricity price by changing the energy supply curve and will affect consumer demand only through its impact on wholesale prices.

Climate data such as temperature, wind speed, and other weather conditions are reported by weather stations on an hourly basis and are available from the Government of Canada. Local economic conditions, such as the monthly unemployment rate, are from Statistics Canada (Statistics Canada 2020). In addition, we collect the future prices for crude oil and natural gas from the Government of Alberta, and future prices for canola and feeder beef from Investing.com, which extracts historical price data from two commodity market in the US: Chicago Mercantile Exchange (CME) and Chicago Board of Trade (CBOT).[26] We gather this information because it can impact a customer's electricity demand decisions. Temperatures significantly influence the need of electricity for heating and cooling (Faruqui and Aydin 2017). Economic conditions, as measured by labor market statistics and commodity prices, can affect the level of business activities and the associated demand for electricity in Lethbridge.

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the pool price) is determined through a bidding process. The generators submit bids to the system operator specifying several price-quantity offer blocks. The system operator will aggregate these offer blocks to create a supply curve based on the descending order of offer prices. The intersection of the electricity demand and the supply curve determines the wholesale price.

26. We select these commodities because these prices can have a significant impact on Lethbridge's economy. As stated in Serecon (2014), agriculture is the primary industry in Lethbridge, and beef feeding made a contribution of $621.5 million to the local economy (55% of the agriculture industry). Canola is one of the major crops in Lethbridge and brought $55 million to the economy. The energy sector is the backbone of Alberta's economy. In 2016, Alberta exported $51.0 billion in energy resources and about 86.1% is crude oil (Alberta Government 2018).

3.4.4 Effect of MDC Rate on Customer Electricity Bills

How customers will respond to an MDC rate change will be determined by how the MDC rate would affect a customer's electricity bills. To understand the magnitude of the MDC rate change, we compare the monthly electricity bills with different MDC rate levels while holding electricity demand constant. Because most customers in our sample incur maximum demand during the summer, we compare the MDC rate levels in 2017 and 2018, the two summer seasons in our sample period. For 996 customers, the MDC rate changed from \$0.4253 per kVA per day in 2017 to \$0.3941 per kVA per day in 2018, reflecting a 7.34% decrease from 2017 to 2018. For 995 customers, the MDC rate was reduced by 8.58% from 2017 to 2018, changing from \$0.4848 per kVA per day to \$0.4432 per kVA per day.

Table 3.2 presents the summary statistics for the electricity consumption of 995 and 996 customers used in our analysis. Both 995 and 996 consumers had lower kWh consumption in 2018 than in 2017. The kWh consumption decreased by 3.0% and 0.4% for 995 and 996 customers, respectively. The daily maximum demand increased by 1.7% for 995 customers and decreased by 2.2% for 996 customers. The annual maximum demand was essentially unchanged between 2017 and 2018.

Figure 3.1 shows the monthly electricity bills for an average 995 and 996 customer under different MDC rate levels during the summer months.[27] We use the kWh and kVA consumption in 2018 as the baseline and calculate the corresponding monthly electricity bills under MDC rate levels in 2017 and 2018. As shown in Figure 3.1, if the 2017 MDC rate were used in 2018, holding consumption constant, the MDCs would increase by \$468.7 and \$645.1 for 995 and 996 customers, respectively. In percentage terms, these changes represent 7.9% and 7.3% of the customer's MDCs and 2.8% and 3.4% of the total electricity bills, respectively.

27. The volumetric charge includes all per kWh charges, including the monthly average wholesale rate, variable distribution and transmission charges, and rate riders. For simplicity, MDCs in a given year are calculated based on the maximum demand within that year.

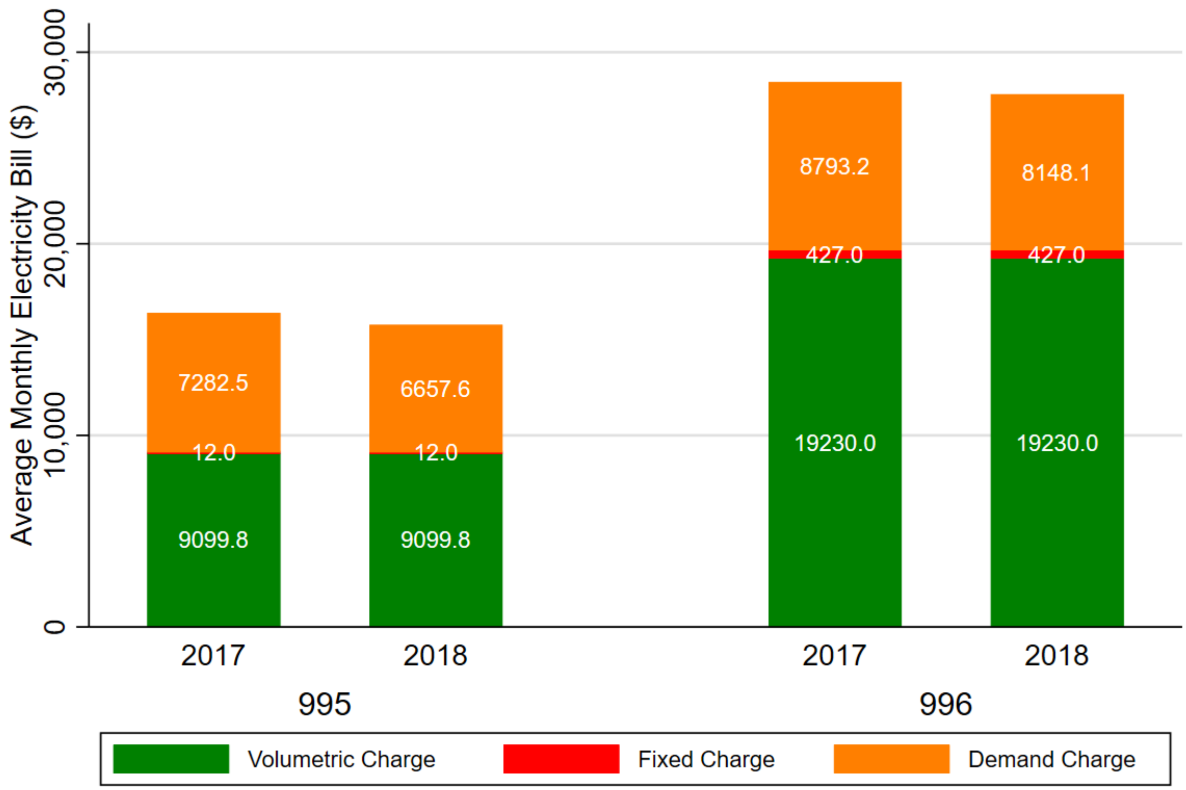

Figure 3.1: MDC Rates and Corresponding Monthly Electricity Bills

Table 3.2: Summary Statistics of Electricity Demand

	995 Customers		996 Customers	
	2017	2018	2017	2018
Daily kWh Mean	3,525	3,419	8,009	7,974
Daily kWh Std. Dev.	1,889	1,771	9,221	9,562
Daily Max kVA Mean	283	288	510	499
Daily Max kVA Std. Dev.	179	220	544	547
Annual Max kVA Mean	460	458	656	657
Annual Max kVA Std. Dev.	274	294	638	646

Figure 3.2 shows the histograms of the percentage bill changes in 2017 if the 2018 MDC rate was applied. Most 995 customers faced a percentage bill change between 3% and 5% if the 2018 MDC rate was used. In comparison, most 996 customers will face a bill change between 2% and 3.5%. The long tails in these figures suggest that some customers face more substantial incentives from the MDC rate change than others. For example, while an average 995 customer can only save 4% of the total electricity bill if the 2018 rate was applied in 2017, one customer could save up to 7%. These numbers suggest that the MDC rate change had a modest impact on 995 and 996 customers between 2017 and 2018.

3.5 Methodology

Our case study aims to estimate the demand response resulting from changes in the MDC rate for large commercial and industrial customers. In particular, we investigate how customers adjust maximum demand when facing an MDC rate decrease. However, unlike energy charges that change monthly, the MDC rate only changes once in our sample period, which makes it difficult to estimate a complete demand curve or related elasticity. As a result, our study

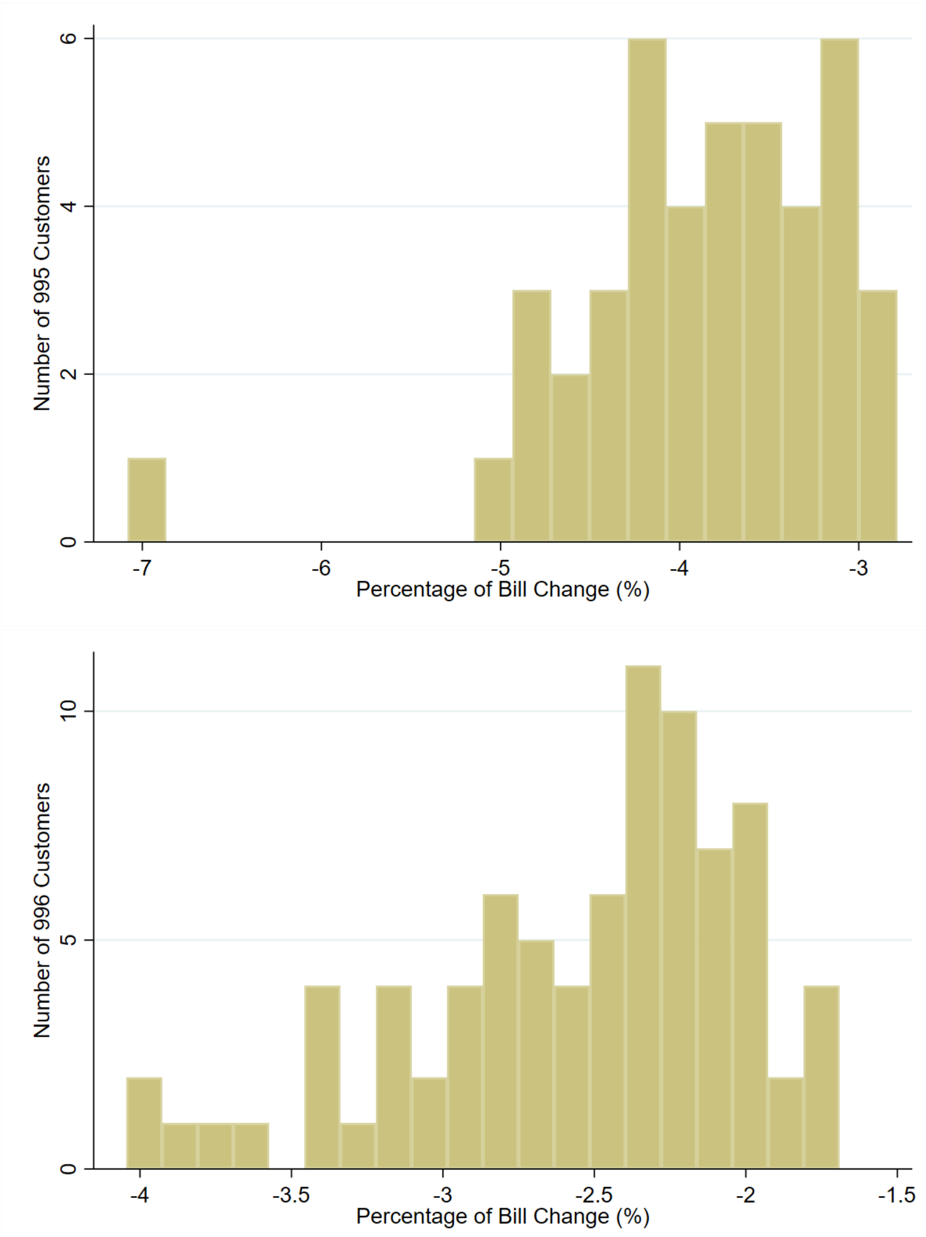

Figure 3.2: Distribution of Percentage Bill Changes Resulting from the MDC Rate Change

focus on comparing customer maximum demand before and after the MDC rate change, controlling for other factors affecting customer demand, such as temperature.

In particular, based on a set of predictor variables, we use machine learning techniques to predict counterfactual electricity demand in 2018 based on electricity demand in 2017, holding the MDC rate unchanged. We then compare the prediction errors before and after the MDC rate change. If customers increase maximum demand after the rate change in 2018, the prediction error will be higher in 2018 than in 2017. In addition, since MDCs are based on maximum demand in a 12-month rolling period, they should only affect electricity demand in a period when maximum demand is likely to occur. As most customers have annual maximum demand during summer times, we divide customers into a summer-peak group and a non-summer-peak group based on a summer-peak ratio[28] using data from 2017 (prior to the MDC change) and investigate how maximum demand changes for each group during the summer months.[29] It is anticipated that the MDCs will only affect maximum demand for summer-peak customers during the summer.

As argued by Burlig et al. (2020), the machine-learning analysis can outperform traditional fixed-effects models in two critical aspects. First, the estimates of the fixed effects model are more sensitive to control variables than the estimates from the machine learning approach. Second, the machine learning approach can avoid certain biases that are common to a fixed effect model. It has been shown that fixed effects models are often inadequate to control for heterogeneity across the subjects (Burlig et al. 2020). This may threaten the validity of the fixed-effects model in our analysis as electricity customers in our sample can exhibit very different behavior patterns that the fixed effects cannot adequately control. Therefore, we use the machine learning approach as the benchmark in our analysis.

28. See Section 3.5.1 for more details.

29. We are unable to perform a formal difference-in-difference analysis because there are no clear boundaries or distinctions between the groups and because the treatment (MDC rate change) is applied to both groups.

In the remainder of this section, we first discuss our classification of summer-peak and non-summer-peak customers. In Section 3.5.2, we provide detailed insight into the machine learning approach employed to generate the counterfactual demand profiles. In Section 3.5.3, we explain how to estimate the demand response based on a before-and-after comparison of prediction errors.

3.5.1 Summer-Peak vs Non-Summer-Peak Group

Most customers in our sample reach annual maximum demand during the summer months. These customers may respond to high temperatures more strongly than customers who have an annual maximum demand in winter. As a result, for a summer-peak customer, the 12-month rolling maximum demand tends to occur during high-temperature days.

A natural first measure to determine whether a customer is a summer-peak customer can simply be the average daily temperature for this customer's highest demand day. If this day coincides with a sufficiently hot day, it is likely that the customer will experience high demand on another hot day. The threshold for what constitutes "sufficiently hot" can be determined by the average daily temperature during the highest temperature day. Therefore, a straightforward initial measure is the ratio between the temperature of the highest demand day and the highest temperature day. When a customer's highest demand day coincides with the highest temperature day, this ratio will be 1.

However, it is possible that a customer can reach maximum demand due to temperature-unrelated demand shocks. For this reason, instead of focusing on a single day, the measure could be based on the highest t days. Formally, a summer-peak customer is defined based on the temperature (measured by the cooling degree days, or CDDs) during the customer's t highest-demand days as a fraction of the temperature during the t hottest days. CDDs are often used to measure the cooling requirements of a given day, and is defined as

$\max\{0°\text{C}, \text{temp}°\text{C} - 18°\text{C}\}$ in Canada, where temp°C is the average temperature of the given day. Formally, a customer is summer-peak if the ratio defined below is equal to or larger than 0.5.[30]

$$\text{Summer-Peak Ratio} = \frac{\sum_{i=1}^{t} \text{CDD}_i}{\sum_{j=1}^{t} \text{CDD}_j} \tag{3.1}$$

where $i = 1, 2, ...$ is a descending rank based on the daily maximum electricity demand, and $j = 1, 2, ...$ is a descending rank based on the daily cooling degree days. When a customer's t highest demand days coincide with the t hottest days in the summer, he will have a summer-peak ratio of 1. If all of the t highest demand days happen during the winter (with 0 CDD), the customer will have a ratio of 0. In the default setting, we let t equal 10. However, changing t to 20 does not change the classification results of the customers in our case study. Figure 3.3 presents the histogram of the summer-peak ratio for 995 and 996 customers, respectively.

Based on the benchmark definition, we find that 41.9% (18 out of 43) of 995 customers and 49.4% (41 out of 83) of 996 customers are summer-peak customers. A small percentage of customers are non-summer customers with a summer-peak ratio of 0. Specifically, 18.6% (8 out of 43) of 995 customers and 13.3% (11 out of 83) of 996 customers are clearly non-summer-peak customers, whose 12-month rolling maximum demand generally occurs during winter months.

3.5.2 The Machine Learning Approach

We use the machine learning approach to create a prediction model for daily maximum demand for each customer in our sample. The goal of the prediction model is to create counterfactual maximum demand that describe what would have happened if the MDC rate change did not exist. We only use data in 2017 to train the prediction model, effectively

30. We conduct robust tests for alternative cut-off values of 0.8 and 0.2, respectively. The main results are similar to the benchmark case.

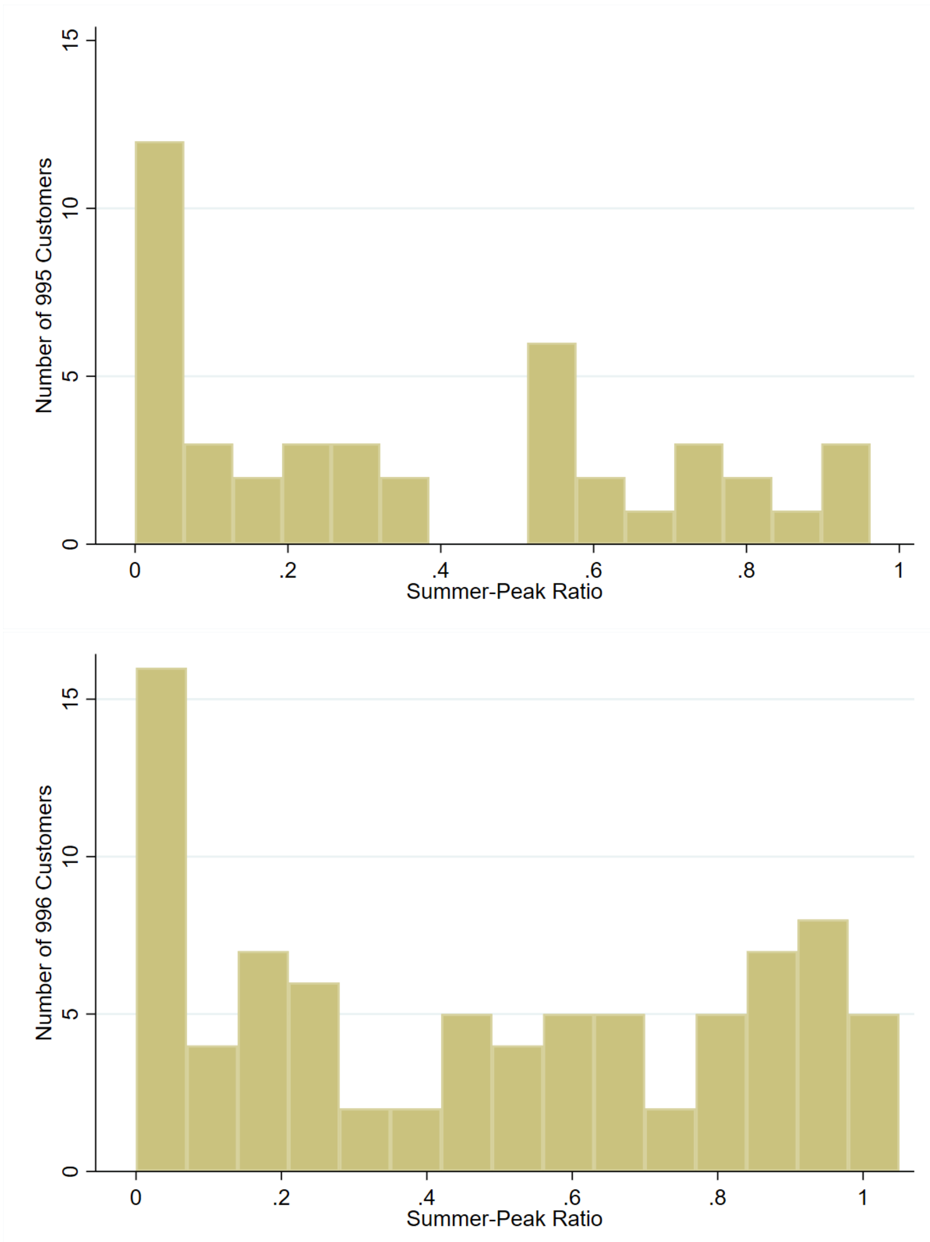

Figure 3.3: Distribution of Summer-Peak Ratio for 995 and 996 Customers

holding MDC rate constant. This allows us to estimate the maximum demand response toward MDCs by comparing the out-of-sample prediction errors across years. In particular, if customers are increasing maximum demand in 2018 given lower MDC rate, the prediction model will underestimate the maximum demand in 2018. Compared to a classic fixed effect model, the machine learning approach allows us to specify prediction models for each customer and provide more robust predictions.[31]

Machine learning techniques are attracting increasing attention across various economic studies. As a significant part of the machine learning toolbox, regularized regression has been widely used for model selection, prediction, and causal inference. Unlike OLS regression, regularized regression imposes a regularization penalty for adding explanatory variables to balance between bias and variance (Ahrens et al. 2020). This feature makes regularized regression a generally better tool than OLS regression regarding out-of-sample prediction. One of the most popular regularized regression approaches is the Least Absolute Shrinkage and Selection Operator (LASSO), which penalizes the absolute size of the coefficient estimates.

LASSO regression was first introduced by Tibshirani (1996) in order to enhance prediction accuracy and perform subset selection when a a large number of predictors exist. It minimizes the residual sum of squares subject to a penalty on the absolute size of coefficient estimates:

$$\widehat{\beta}_{lasso}(\lambda) = argmin \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i^{'}\beta)^2 + \frac{\lambda}{n}\sum_{j=1}^{p}\psi_j \left|\beta_j\right| \tag{3.2}$$

Compared to the OLS estimator, the LASSO estimator contains a second part as a regularization penalty. The overall penalty level is controlled by λ (tuning parameter), and ψ_j is the predictor-specific penalty loading. There is usually no predictor-specific penalty loading,

31. Appendix C provides the corresponding methodology and results for a fixed-effect approach.

and ψ_j will be set to one.[32]

LASSO Prediction models have three advantages compared to traditional prediction methods based on the OLS estimator. First, LASSO prediction models have significantly better prediction accuracy than traditional prediction methods by balancing between bias and variance (Ahrens et al. 2020). Second, LASSO prediction models can better capture heterogeneity between customers by self-selecting the best prediction model for each customer (Burger et al. 2020). This is important in estimating the maximum demand of the customer, as different customers can exhibit different demand patterns. Third, LASSO prediction models can often produce more robust results than traditional prediction methods (Burger et al. 2020). In contrast, traditional prediction methods are very sensitive to different selections of prediction variables, leading to a complicated model selection process, especially when faced with a large set of potential prediction variables. Machine learning techniques have been used for load prediction (e.g., Fan et al. 2014), but our paper is the first to use such technologies to analyze the MDC responses.

To examine how maximum demand changes from 2017 to 2018 as the MDC rate changes, we forecast each customer's daily maximum demand during the summer months using machine learning techniques. The machine learning algorithms will help us select the best prediction model from a large set of potential explanatory variables. The prediction model has the following structure but will only include appropriate prediction variables based on the extended Bayesian information criteria (EBIC)[33]:

$$D_{it} = \gamma_{i1}T_t + \gamma_{i2}T_t^2 + \gamma_{i3}T_t^3 + \gamma_{i4}T_t^4 + \beta X + \delta Z + \varepsilon_{it} \tag{3.3}$$

32. Generally, setting ψ_j to one maintains simplicity and consistency for the LASSO estimator, making it easier to apply and interpret the regularization process in LASSO regression (Ahrens et al. 2020).

33. Compared to Bayesian information criteria (BIC), EBIC constrain the number of unknown parameters, and limit the model space, which provides a more stringent way to select the appropriate λ in Equation (3.2), reducing the likelihood of over-fitting (Chen and Chen, 2008).

where D_{it} represents the daily maximum demand in kVA for the customer i in day t. We estimate kVA demand at the daily level as the MDCs are based upon the highest daily maximum demand in 12 months. Compared to estimating at the hourly level, a daily level estimation can enhance the prediction accuracy of the model and is commonly used for estimating maximum demand (Gibbons and Faraqui, 2014).

T_t is the CDD in day t. Temperature is widely considered a key variable for forecasting electricity demand due to the high penetration of electrical cooling and heating. We include the first to fourth temperature polynomial to capture the nonlinearity effects of temperature on daily maximum demand. X stands for other control variables, such as wind speed, rainfall, snowfall, daylight hours, humidity, visibility, commodity prices for crude oil, natural gas, feeder beef and canola, and unemployment rate. We use the cluster-robust covariance estimator (sandwich estimator) and clustered standard errors on the customer level to correct autocorrelation and heteroskedasticity in the residuals.

The selected control variables can have important impacts on electricity demand. Wind speed can influence the electrical demand as higher wind speed will increase the heating loss for buildings. Longer daylight hours will decrease facilities' lighting and heating needs, reducing the electrical demand. The unemployment rate and commodity prices for crude oil, feeder beef, and canola are important economic indicators for Lethbridge, which can significantly impact industrial and commercial customers. Natural gas commodity prices are an important proxy for the electricity prices faced by large industrial and commercial customers, as natural gas generators are the backbone of Alberta's electricity generation fleet, and changes in wholesale electricity prices largely follow the changes in natural gas costs (MSA, 2018). Z stands for time dummy variables for the day of the week, holidays, and the month of the year.

The goal of the prediction model is to create counterfactual electricity demands that describe what would have happened if the MDC change did not exist. Therefore, we only use data from 2017 to "train" the model. To understand the in-sample and out-of-sample prediction accuracy, we randomly selected 70% of the summer days in 2017 to "train" the model and validate the model on the remaining 30% of days. Because we only have complete data in summer months for both 2017 and 2018, we focus on summer days and compare between summer-peak and non-summer-peak customers. We include non-summer-peak customers as a placebo test because they are not likely to incur maximum demand during this period and have no incentives to adjust daily maximum demand.

The general goodness of fit measure for the prediction models can be measured by the in-sample and out-of-sample Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right|$$

where y_i is the daily maximum demand for each customer.

3.5.3 Before-After Comparison

The next step of our analysis is to compare the counterfactual consumption profiles with the observed meter data. However, since counterfactual consumption is subject to prediction errors, we cannot directly compare it with actual consumption. Instead, we focus on the prediction errors before and after the MDC change. If the MDC change causes a substantial behavioral change, the prediction errors after the change will differ because the prediction errors after the MDC change can capture both the model errors and the change in actual demand behavior. If the model errors are consistent before and after the MDC change, the changes in prediction errors will imply a change in the daily maximum demand.

To assess whether changes in prediction errors are caused by the MDC rate change and not just model forecast errors, we conduct a placebo test by randomly assigning dates in 2017 into a "pre" and a "post" period. We then follow our standard machine learning procedure to obtain prediction errors for each period. Because the "structural break" between periods (pseudo "years") does not actually exist, any differences in prediction errors across periods can be attributed to model errors. If the model prediction is consistent across time after controlling for temperature and economic conditions, we anticipate that the differences in prediction errors across periods will be statistically insignificant and close to zero. The results of the placebo test are provided in Section 3.6.2.

For summer-peak customers, if the prediction errors are higher in 2018 than in 2017 during hot days, customers are increasing maximum demand. This could be because a lower MDC rate reduces the costs of having a higher maximum demand. In contrast, if the prediction errors in 2018 are lower than those in 2017, customers are reducing the maximum demand, further reducing the electricity bills they face by utilizing the MDC. For non-summer-peak customers, if the prediction model is well specified, we expect the difference in prediction errors during summer days to be close to zero and insignificant.

If a customer has perfect information regarding when maximum demand will occur, comparing the annual maximum demand across years, controlling for other related factors, can reveal the effects of the MDC rate on maximum demand. However, in reality, customers often do not know when maximum demand will occur, so they might adjust maximum demand whenever they feel a day may become the peak day of a year. For summer-peak customers, this usually happens when the days are sufficiently hot. The probability of hitting the maximum demand increases as the temperature increases. As a result, customers face stronger motivations to adjust peak demand as days get hotter, or as their daily maximum demand gets higher. For this reason, we divide each customer's daily maximum demand into five temperature quantiles for each year and compare the prediction errors in each quantile. Formally, we use the following fixed effects model with cluster-robust standard errors to compare the prediction errors across time:

$$error_{it} = \sum_{q}^{5} \gamma_{q=2} Q_{qt} + \sum_{q}^{5} \delta_{q=2} Q_{qt} * \mathit{Year}_{2018} + \mathit{Year}_{2018} + \mathit{In\text{-}sample}_{it} + \varepsilon_{it} \tag{3.4}$$

where $error_{it}$ is the prediction error in percentage terms calculated as the actual logged kVA minus predicted logged kVA. Q_{qt} is the factorial variable for the qth temperature quantile. $Year_{2018}$ is the dummy variable for the year 2018. The difference in prediction errors across years for different quantiles are captured by δ_q. If customers respond to the demand change, at least one of the δ_q should differ from zero. As summer customers are more likely to respond to the demand change when daily maximum demand is sufficiently high, δ_5 should be more likely to be significant and differ from zero. For non-summer customers, we expect all δ_q to be close to zero. As the in-sample prediction errors tend to differ from the out-of-sample errors, we use *In-sample*$_{it}$, which is an indicator for in-sample observation, to recenter the in-sample and out-of-sample errors toward zero.

Our empirical strategy can be summarized as follows. If customers do not respond to the MDC change, the prediction errors will only reflect the lack of prediction accuracy due to the prediction power of the model. If the prediction power before and after the MDC change are similar (e.g., no time-variant error caused by omitted variables), there will be no substantial changes in the prediction errors. If customers do respond to the MDC change by adjusting their maximum demand, the prediction errors after the MDC rate change will also reflect this behavioral change. In addition to the MDCs, other unobservable factors can also affect maximum demand, and it is challenging to establish a causal relationship between MDC rate and customer behavior (Öhrlund et al. 2019). Our empirical strategy uses the narrow time window to identify the potential effect of MDCs, as MDCs will only affect maximum demand on certain high-demand days. In addition, we utilize the comparison between summer-peak and non-summer-peak customers because the MDC rate change should only affect the summer-peak customers. However, our strategy will not capture the effects of MDCs on energy conservation investments, as most energy conservation technology can reduce electricity demand on both high-demand and low-demand days.

3.6 Results

3.6.1 Model Performance

The model's prediction accuracy is measured by the in-sample and out-of-sample MAE and MAPE in 2017, which is presented in Table 3.3. We reestimate Equation (3.3) using the OLS estimator on the same training data to examine how the LASSO prediction model compared with the traditional OLS prediction model. As shown in Table 3.3, the LASSO estimator provides better out-of-sample prediction accuracy than the OLS estimator at the cost of lower in-sample MAPE, reflecting a potential overfitting problem of training data in the OLS regression. The average in-sample and out-of-sample MAPE using the LASSO prediction model is 5.4% and 6.6% for 995 customers. The model performs slightly better for 996 customers, with an in-sample and out-of-sample MAPE of 3.9% and 5.2%, respectively.

Table 3.3: Summary of MAE and MAPE

995	2017 In-sample		2017 Out-of-sample	
	MAE	MAPE	MAE	MAPE
LASSO	13.2	5.4%	16.0	6.6%
OLS	11.8	4.7%	18.0	7.4%
996	2017 In-sample		2017 Out-of-sample	
	MAE	MAPE	MAE	MAPE
LASSO	15.2	3.9%	17.8	5.2%
OLS	13.0	3.0%	20.2	5.8%

Given the complexity of predicting individual maximum demand, previous studies obtained a wide range of prediction MAPEs using various prediction models. Our prediction models perform similarly to these studies. For example, Ke et al. (2016) predicted the maximum demand of a campus building using polynomial regression, and the resulting MAPE is 3.37%. Fan et al. (2019) predicted the maximum demand for residential buildings using a general linear model and obtained a MAPE of 4.6%. Kim et al. (2022) estimate the daily maximum demand for residential customers using artificial neural networks and get an average MAPE of 11.7%. Taheri and Razban (2022) use a probabilistic regression model to forecast daily maximum demand for commercial and manufacturing buildings and obtain an average MAPE of 9.3%.

3.6.2 Before-After Maximum Demand Comparison

Table 3.4 presents the estimation results of Equation (3.4) for 995 customers. Columns (1) and (2) present the results for summer-peak and non-summer-peak customers, respectively. Columns (3) and (4) add temperature controls to the estimation equation, which aims to control for prediction errors that correlate with the daily temperature. The coefficients of interest are the interactions between the quantiles and the year 2018, which captures the difference in daily maximum demand between 2017 and 2018 in percentage terms. For example, the first column suggests that, on average, a summer-peak customer's daily maximum demand increased by 3.1% in 2018, but it is not statistically significant.

As shown in Table 3.4, controlling for temperature, a summer-peak customer's daily maximum demand increased on average by 4% in 2018 in the 5th demand quantile. This implies that medium-sized summer-peak customers have higher maximum demand in 2018 (with a lower MDC rate) when the annual maximum demand is likely to occur. In comparison, as anticipated, the changes in maximum demand from 2017 to 2018 are insignificant for non-summer-peak customers. We conduct a Wald test to test for the equality of the two coefficients of interest from columns (2) and (4) within the framework of a seemingly unrelated regression. The null hypothesis that the two coefficients are equal is rejected at a 0.1% significance level. The results show that customers may increase maximum demand when faced with a lower MDC rate. However, due to data limitations, it is challenging to infer a causal relationship between MDC rate change and changes in maximum demand.

Table 3.4: Panel Fixed Effects Results - 995 Customers

	(1) Error	(2) Error	(3) Error	(4) Error
5th Quantile * 2018	0.031	-0.006	0.040**	0.007
	(0.019)	(0.053)	(0.019)	(0.055)
4th Quantile * 2018	0.020	-0.056	0.023	-0.043
	(0.022)	(0.049)	(0.023)	(0.052)
3rd Quantile * 2018	0.031	-0.009	0.028	-0.000
	(0.018)	(0.039)	(0.020)	(0.039)
2nd Quantile * 2018	0.027	-0.010	0.033	-0.001
	(0.020)	(0.051)	(0.031)	(0.042)
5th Quantile	0.104***	0.251***	0.127**	0.249***
	(0.034)	(0.039)	(0.047)	(0.040)
4th Quantile	0.061**	0.191***	0.076*	0.185***
	(0.030)	(0.046)	(0.041)	(0.048)
3rd Quantile	0.037	0.114**	0.045	0.109**
	(0.024)	(0.041)	(0.030)	(0.043)
2nd Quantile	0.022*	0.086*	0.039	0.097**
	(0.010)	(0.041)	(0.027)	(0.033)
Year (2018)	-0.072***	0.045	-0.081***	0.037
	(0.024)	(0.047)	(0.023)	(0.049)
Summer-Peak Customers	Yes	No	Yes	No
Add Temperature Controls	No	No	Yes	Yes
Observations	1,136	1,471	1,136	1,471

Notes: This table presents the estimation results of Equation (3.4) for 995 customers. The dependent variable is prediction error. The 2nd, 3rd, 4th, and 5th quantiles represent different quantiles in daily maximum temperatures, with the 5th quantile indicating the hottest 20% days. Columns (1) and (2) present the estimation results for summer-peak and non-summer-peak customer groups, respectively. Columns (3) and (4) present the same estimation results but with additional control for temperature variables. Std. Dev. in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.5 presents the estimation results for 996 customers. Unlike 995 customers, all coefficients of interest are insignificant. An insignificant result can suggest two possibilities. First, the null hypothesis is true, and there is no real effect. Second, the null hypothesis is not true, but we do not have sufficient evidence to reject it due to sample limitations. In our case study, it is challenging to rule out the second possibility due to data limitations. More data is needed to support the evidence that large customers do not respond to MDC rate decreases.

MDCs can have a more substantial impact on larger customers, leading to stronger incentives to reduce maximum demand. This could potentially explain why larger customers do not respond to a decrease in the MDC rate. Faced with high MDC bills, larger customers have more substantial incentives to invest in energy conservation or load-shifting technologies, such as batteries. Therefore, it is likely that these customers have already responded to the MDCs before. The remaining electricity demand could be largely inflexible, leading to minimum responses.

These findings suggest a possible asymmetric response to changes in MDC rates. When MDC rates increase, customers may be inclined to make significant investments in energy conservation or demand-shifting technologies, which could become sunk costs and represent a long-term commitment to reducing maximum demand. Conversely, when MDC rates decrease, the response might be limited to short-term behavioral adjustments, such as modifying cooling or heating needs, which generally have a smaller impact. This potential asymmetry highlights the complexity of customer behavior in response to MDC rate changes and underscores the need for more nuanced tariff designs that account for these varying responses.

Table 3.5: Panel Fixed Effects Results - 996 Customers

	(1) Error	(2) Error	(3) Error	(4) Error
5th Quantile * 2018	-0.019	-0.014	-0.015	-0.006
	(0.014)	(0.019)	(0.014)	(0.019)
4th Quantile * 2018	-0.010	-0.001	-0.012	0.004
	(0.014)	(0.021)	(0.013)	(0.021)
3rd Quantile * 2018	-0.013	-0.013	-0.022	-0.010
	(0.016)	(0.018)	(0.015)	(0.018)
2nd Quantile * 2018	-0.016	-0.015	-0.018	-0.007
	(0.018)	(0.018)	(0.020)	(0.019)
5th Quantile	0.096***	0.211***	0.146***	0.214***
	(0.016)	(0.028)	(0.023)	(0.028)
4th Quantile	0.068***	0.152***	0.102***	0.155***
	(0.013)	(0.023)	(0.018)	(0.023)
3rd Quantile	0.056***	0.109***	0.076***	0.111***
	(0.015)	(0.021)	(0.018)	(0.021)
2nd Quantile	0.044***	0.097***	0.066***	0.099***
	(0.013)	(0.017)	(0.015)	(0.016)
Year (2018)	-0.028***	0.005	-0.081***	-0.005
	(0.018)	(0.016)	(0.023)	(0.023)
Summer-Peak Customers	Yes	No	Yes	No
Add Temperature Controls	No	No	Yes	Yes
Observations	2,289	2,861	2,289	2,861

Notes: This table presents the estimation results of Equation (3.4) for 996 customers. The dependent variable is prediction error. The 2nd, 3rd, 4th, and 5th quantiles represent different quantiles in daily maximum temperatures, with the 5th quantile indicating the hottest 20% days. Columns (1) and (2) present the estimation results for summer-peak and non-summer-peak customer groups, respectively. Columns (3) and (4) present the same estimation results but with additional control for temperature variables. Std. Dev. in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Placebo Test

This section presents the results of the placebo test, where only the pre-treatment data are used to develop the prediction model. This allows us to isolate the effects of the MDC rate change and focus on the prediction model's inherent error. The main results of our paper will be robust if the model error is close to zero.

Table 3.6 presents the fixed effects model for the prediction errors of the placebo test. Columns (1) through (4) correspond to summer-peak 995 and 996 customers with and without temperature controls, respectively. As shown in Table 3.6, all coefficients capturing the prediction error differences between the "pseudo" pre- and post-treatment periods are statistically insignificant. These results suggest that the model error is unlikely to significantly affect the main findings in our paper.

Table 3.6: Placebo Test - 995 and 996 Customers

	(1)	(2)	(3)	(4)
	995	995	996	996
5th Quantile * 2018	0.006	-0.006	-0.000	-0.003
	(0.013)	(0.125)	(0.003)	(0.004)
4th Quantile * 2018	0.021	0.000	0.000	-0.006**
	(0.014)	(0.014)	(0.003)	(0.003)
3rd Quantile * 2018	0.011	-0.001	-0.000	-0.004
	(0.012)	(0.018)	(0.004)	(0.003)
2nd Quantile * 2018	-0.000	-0.006	-0.003	-0.007
	(0.013)	(0.011)	(0.004)	(0.003)
5th Quantile	0.081***	0.152***	0.071***	0.115***
	(0.013)	(0.022)	(0.006)	(0.007)
4th Quantile	0.043***	0.096***	0.055***	0.083***
	(0.011)	(0.018)	(0.006)	(0.005)
3rd Quantile	0.035***	0.065***	0.034***	0.049***
	(0.014)	(0.016)	(0.004)	(0.004)
2nd Quantile	0.027***	0.042***	0.030***	0.044***
	(0.009)	(0.010)	(0.004)	(0.004)
Placebo Year (2018)	-0.007	-0.005	0.004	0.000
	(0.010)	(0.010)	(0.151)	(0.002)
Summer-Peak Customers	Yes	Yes	Yes	Yes
Add Temperature Controls	No	Yes	No	Yes
Observations	1,808	1,808	2,861	2,861

Notes: This table presents the estimation results of the placebo test. The dependent variable is prediction error. The 2nd, 3rd, 4th, and 5th quantiles represent different quantiles in daily maximum temperatures, with the 5th quantile indicating the hottest 20% days. Columns (1) and (2) present the estimation results for 995 customers with and without temperature controls, respectively. Columns (3) and (4) present the same estimation results for 996 customers. Std. Dev. in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.7 Conclusion

Our paper reviews the literature on the current debate as to whether MDC can provide fair and efficient fixed-cost recovery for utilities. We discussed how future studies should be conducted to provide further evidence for the debate. In addition, as a key motivation for the MDCs, we investigated how customers respond to MDCs by reviewing the related studies and, finally, conducted a case study to study how medium and large customers respond to an MDC rate decrease.

In terms of customer responses, existing studies find that customers will reduce maximum demand when faced with MDCs. However, how customers adjust maximum demand when the MDC rate decreases has not been investigated. In theory, customers may increase maximum demand because it is less expensive to do so with a lower MDC level. The opposite can also be true because the decrease in MDC rates is temporary and customers may still be in a learning phase to reduce maximum demand. By doing a case study, we find limited evidence that large customers will increase or decrease maximum demand when faced with a lower MDC rate. We show that medium-sized customers exhibit a higher maximum demand when the MDC rate is lower. These findings may be explained by an asymmetric response to MDC rate changes, where increases in MDCs can motivate both investment and behavioral changes, while decreases in MDC rates typically do not lead to significant changes because investments have already been sunk and demand responses are limited to temporary behavioral changes. However, due to the data limitations of our study, future work is needed to reassess the causal relationship between the MDC rate level and customer maximum demand.

From an economic point of view, the volumetric charge should reflect the time-varying costs of generating electricity. Recovering fixed costs using volumetric charges will lead to inefficient consumption decisions and cross-subsidy concerns. Economic theory suggests that fixed costs should be recovered through fixed charges (Borenstein 2016). However, increasing fixed charges can have substantial distributional effects and face severe political barriers. An income-based fixed charge can alleviate some of the distributional concerns associated with a universal increase in fixed charges. However, designing efficient and fair income-based fixed charges would require household-level income data, which may be challenging for some jurisdictions.

As an alternative to higher fixed charges, MDCs are favored by utilities for several reasons. The most important reason is that it can reduce utilities' reliance on volumetric charges to recover fixed charges, reducing cross-subsidy concerns, and providing better cost recovery for utilities (Hledik 2014). At the same time, compared to a tariff with higher fixed costs, MDCs can reduce the distributional effects between smaller and larger customers, leading to fewer political obstructions (Wood et al. 2016). However, although there is some evidence that smaller customers tend to be low-income customers, the correlation can become weaker in the future, since energy conservation and DER technologies are more accessible for high-income customers. Therefore, it could be more economically efficient to directly target low-income customers through social programs (Wood et al. 2016).

The second reason is that MDCs can better align customer billing with the cost structure of utilities, leading to fairer cost recovery. However, around 80% of the costs related to investments in generation, distribution, and transmission capacity are sunk (Passey et al. 2017). From an economic point of view, sunk costs should be recovered using fixed charges as the price signal for the efficient use of the electric grid should be based on long-run marginal costs only (Brown et al. 2015; Borenstein 2016). However, in the future, with increasing electrification, the unsunk part of LRMC for distribution services is expected to increase, and MDCs could play a role in recovering this part of the costs.

The third reason is that MDCs can be used to reduce system maximum demand, leading to lower system investment costs. Existing studies generally find that customers will reduce maximum demand when facing the MDCs. However, as most MDCs are targeting customers' individual maximum demand, whether MDCs can be used to curtail system peak demand will also be determined by whether a customer's individual peak demand coincides with the system peak demand. However, most studies find that non-coincide MDCs are ineffective at reducing system maximum demand compared to other tariff designs with the same goal, such as CPP.

In the short run, MDCs can be used to address some of the current challenges (e.g., cross-subsidies) faced by the utilities. However, more effective tariff designs could exist in the long run: use real-time pricing to recover volumetric charges, set transmission and distribution charges at their long-run marginal cost level, use fixed charges to recover other fixed charges, and use social programs to address distributional concerns.

Future studies are needed to assess the efficiency of MDCs in fulfilling their objectives compared to alternative tariff designs. First, further research is needed to assess the effectiveness of various MDC designs in reducing maximum demand for various customer classes. In particular, for residential consumers, these studies play a crucial role in understanding how MDCs can be designed to optimize the social benefits of DERs. Additionally, for larger consumers, these studies can offer insights into designing more efficient demand response programs.

Second, the evidence regarding whether MDCs can offer more cost-reflective recovery is scarce in the literature. In particular, to what extent can current MDC rates reflect the locational long-run marginal costs of the electric network system has not been explored.

Finally, in terms of distributional effects, it is crucial to explore how MDCs impact consumer electricity bills compared to alternative tariff designs (e.g., income-based fixed charges). Specifically, as new technologies such as batteries become more affordable for higher-income consumers and can significantly influence MDCs, it is essential to assess the distributional effects of MDCs in an environment with expanding penetration of DERs.

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3.8 Appendices

Appendix A: Rate Class

The rate classes in Lethbridge are designed to align the distribution and transmission charges of a customer to the costs he incurred on the grid based on his service of distribution and kVA demand. Since 2013, the City of Lethbridge adopts the following rate classes as shown in Table 6 (City of Lethbridge Electric Utility, 2012 to 2019). 991 customers are residential customers. 992 customers are large residential and small commercial customers. 994 customers are medium-sized commercial customers. 995, 996 and 997 customers are large commercial or industrial customers.

Table 3.7: Rate Classes in Lethbridge

Rate Code	Rate Distribution Name	Phase Service	Demand Conditions
991	Standard Single Phase[34]	Single	less than 12 kVA
992	Medium Single Phase	Single	12 kVA or higher
994	General Three Phase[35]	Three	less than 150 kVA
995	Medium Three Phase	Three	between 150 and 300 kVA
996	Large Three Phase	Three	300 kVA or higher
997	Primary	Primary	less than 6 mVA

Appendix B: Temperature and Demand

One of the key factors used to predict daily peak demand in our study is the daily temperature, measured by the daily cooling degree days (CDD). To what extent can daily

34. Single Phase service uses two wire Alternating Current (AC) power circuit. It is the most common household power circuit that powers lights, TV, etc.

35. Three Phase service uses three wire Alternating Current (AC) power circuit. Most commercial buildings use this power arrangement because it provides higher power density and flexibility than a single phase service.

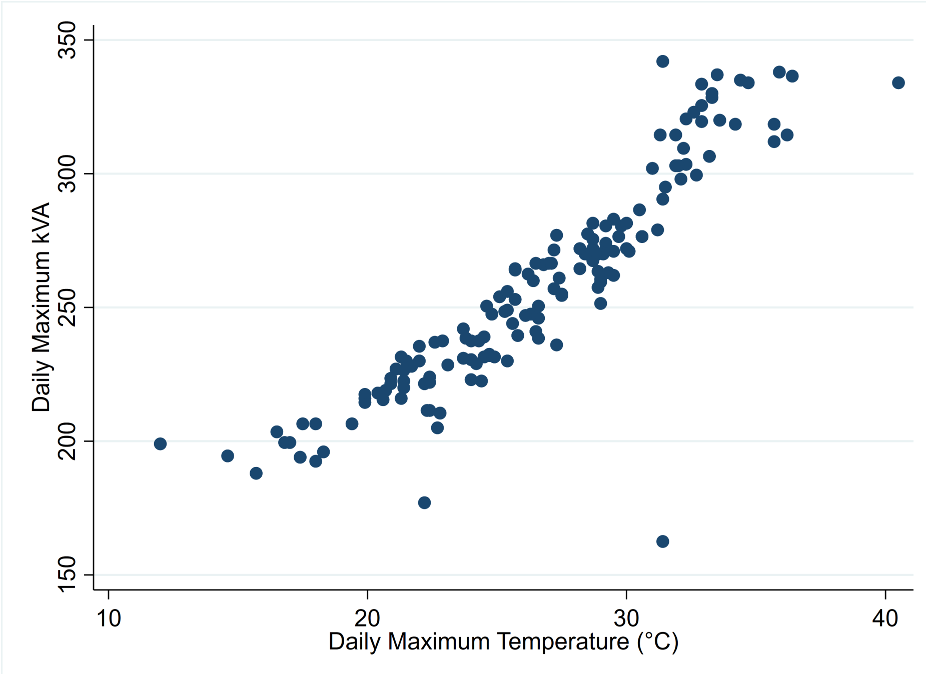

Figure 3.4: Relationship Between Temperature and Demand for a Summer-Peak Customer

temperature determine daily peak demand is key in determining the performance of our prediction model. As an illustration, Figure 3.4 plots the relationship between daily maximum temperature and daily maximum demand for a typical summer-peak customer. This section investigates the relationship between temperature and demand by using a simple fixed effects model:

$$D_{it} = \gamma_1 CDD_t + \gamma_2 CDD_t^2 + \beta X + \varepsilon_{it} \tag{3.5}$$

where D_{it} is the daily maximum demand, CDD_t is the daily cooling degree days, and X includes dummy variables for weekends and holidays. The results are presented in Table 3.8. Columns (1) and (2) show the estimation results for summer-peak and non-summer-peak 995 customers, respectively. For summer-peak customers, a one-degree Celsius increase in CDD will increase daily peak demand by 21.4 kVA, or approximately 7.5% of the average daily peak demand. The relatively high within R-square (0.3371) for summer-peak 995 customers suggests that variations in peak demand can largely be explained by variations in CDD. For non-summer-peak 995 customers, a one-degree increase in CDD will increase average daily peak demand by 15.6 kVA. However, the relatively low R-square suggests that other factors, which might not easily be controlled, can significantly affect daily peak demand. Similarly, for 996 customers, an increase in CDD will significantly increase daily peak demand, but the effects are smaller in percentage terms compared to 995 customers. Moreover, the relatively low R-square suggests that variation in CDD alone can only capture a small portion of variations in the daily peak demand. These results suggest that our prediction model will be more accurate for summer-peak 995 consumers than for 996 consumers. Therefore, the main findings in our case study could be more robust for 995 consumers.

Table 3.8: Daily Maximum Temperature vs. Daily Maximum Demand

	(1)	(2)	(3)	(4)
	995	995	996	996
CDD	21.42***	15.58***	24.70***	18.00**
	(3.08)	(3.55)	(-1.54)	(7.31)
CDD^2	-1.44***	-1.76***	-1.54***	-1.48**
	(0.39)	(0.37)	(0.20)	(0.58)
Weekend	-17.48***	-127.38***	-25.97*	-121.54***
	(5.03)	(31.90)	(13.63)	(31.70)
Holiday	-9.04	-102.87***	-25.12	-118.05***
	(5.85)	(19.60)	(15.03)	(32.13)
Constant	222.62***	314.90***	466.18***	547.00***
	(2.65)	(5.12)	(3.43)	(7.94)
Summer-Peak Customers	Yes	No	Yes	No
Observations	2,186	4,583	6,624	7,728
R-square Within	0.3371	0.0741	0.0802	0.0470
R-square Between	0.0350	0.0281	0.0000	0.0000
R-square Overall	0.1202	0.0436	0.0037	0.0092

Notes: This table presents the estimation results of Equation (3.5) for 995 and 996 customers. The dependent variable is the daily peak kVA. CDD is the daily cooling degree days, measured in degree Celsius. Std. Dev. in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix C: Fixed Effects Approach

This section reports the estimation results for the fixed-effects approach. Similar to the machine-learning approach described in Section 3.5.2, the fixed-effects approach utilizes the fact that MDCs are based solely on the 12-month rolling maximum demand. Therefore, after controlling for a set of covariates such as temperature, weekends, holidays, and economic conditions, the differences in daily maximum demand across years should be insignificant for periods when the annual maximum demand is unlikely to occur. Formally, we estimated the following fixed-effects model:

$$D_{it} = \sum_{q}^{5} \gamma_q Q_{qt} + \sum_{q}^{5} \delta_q Q_{qt} * Year_{2018} + Year_{2018} + X_{it} + \varepsilon_{it} \tag{3.6}$$

where D_{it} is the the logged daily maximum demand measured in kVA. Q_{qt} is the factorial variable for the qth temperature quantile. $Year_{2018}$ is the dummy variable for the year 2018. X includes a set of covariates such as daily cooling degree days, time dummy variables for weekend and holidays, and local economic conditions (commodity prices and labor market statistics). The difference in daily maximum demand across years for different quantiles are captured by δ_q. If customers respond to the demand change, δ_5 should be significant and differ from zero. For non-summer customers, we expect all δ_q to be close to zero.

The estimation results are presented in Table 3.9. Consistent with our benchmark results obtained using the machine-learning approach, the average daily maximum demand in the 5th quantile is significant and is 5.7% higher in 2018 compared to 2017 for summer-peak 995 customers. This suggests that customers increase their daily maximum demand when facing a lower MDC rate. In contrast, for non-summer-peak customers, the daily maximum demand remains similar across years. In the machine-learning approach, for 996 customers, the differences in daily maximum demand across years are insignificant at the 5th quantile. However, the fixed effects approach shows that 996 customers exhibit a similar increase in demand when facing a lower MDC rate. Notably, as illustrated in Table 3.9, aside from the 5th quantile, the 4th quantile for summer-peak 995 customers and non-summer-peak 996 customers is also significant. This underscores the heightened sensitivity of the fixed effects model compared to the machine-learning approach, as discussed in (Burlig et al. 2020). For this reason, we take the machine-learning results as the benchmark results in our study.

Table 3.9: Fixed Effects Approach Results

	(1)	(2)	(3)	(4)
	log kVA	log kVA	log kVA	log kVA
5th Quantile * 2018	0.057**	-0.000	0.034*	-0.043
	(0.021)	(0.033)	(0.020)	(0.030)
4th Quantile * 2018	0.041*	-0.010	0.016	-0.056*
	(0.021)	(0.033)	(0.019)	(0.030)
3rd Quantile * 2018	0.020	-0.011	-0.004	-0.037
	(0.180)	(0.046)	(0.018)	(0.027)
2nd Quantile * 2018	0.011	-0.016	-0.010	-0.045
	(0.159)	(0.057)	(0.022)	(0.039)
5th Quantile	0.490***	1.202***	0.424***	0.836***
	(0.060)	(0.144)	(0.074)	(0.115)
4th Quantile	0.390***	1.038***	0.357***	0.752***
	(0.053)	(0.139)	(0.068)	(0.116)
3rd Quantile	0.309***	0.919***	0.291***	0.658***
	(0.047)	(0.138)	(0.060)	(0.108)
2nd Quantile	0.288***	0.875***	0.237***	0.598***
	(0.032)	(0.121)	(0.053)	(0.088)
Year (2018)	-0.109***	-0.001	-0.085***	0.027
	(0.023)	(0.037)	(0.021)	(0.032)
Rate Code	995	995	996	996
Summer-Peak Customers	Yes	No	Yes	No
Observations	3,246	4,261	6,502	8,320

Notes: This table presents the estimation results of Equation (3.6) for 995 and 996 customers. The 2nd, 3rd, 4th, and 5th quantiles represent different quantiles in daily maximum temperatures, with the 5th quantile indicating the hottest 20% days. Std. Dev. in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix D: Load Profiles

In our sample, differences in load profiles across customers are substantial, making it challenging to create a representative load profile. Figure 3.5 shows the load profile for a randomly selected customer during the summer months of 2017 and 2018.

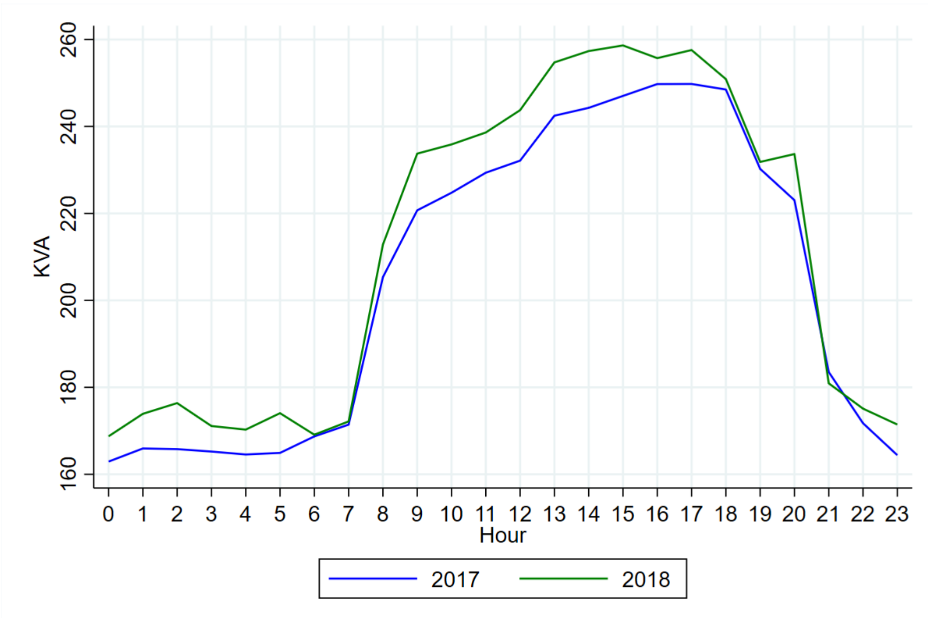

Figure 3.5: Load Profile of a Random 995 Customer

Appendix E: System Maximum Demand and Customer-Specific Maximum Demand

This section explores the correlation between customer-specific maximum demand and Alberta's system maximum demand. First, we examine the correlations between customer-specific load and system load. For 995 customers, the correlation ranges from 0.07 to 0.71, with an average of 0.39. For 996 customers, the correlation ranges from -0.27 to 0.72, averaging at 0.28.

During our sample period, Alberta's system load peaked in February. Figures 3.6 and 3.7 present the relative frequency of when the annual system peak for a customer occurs in

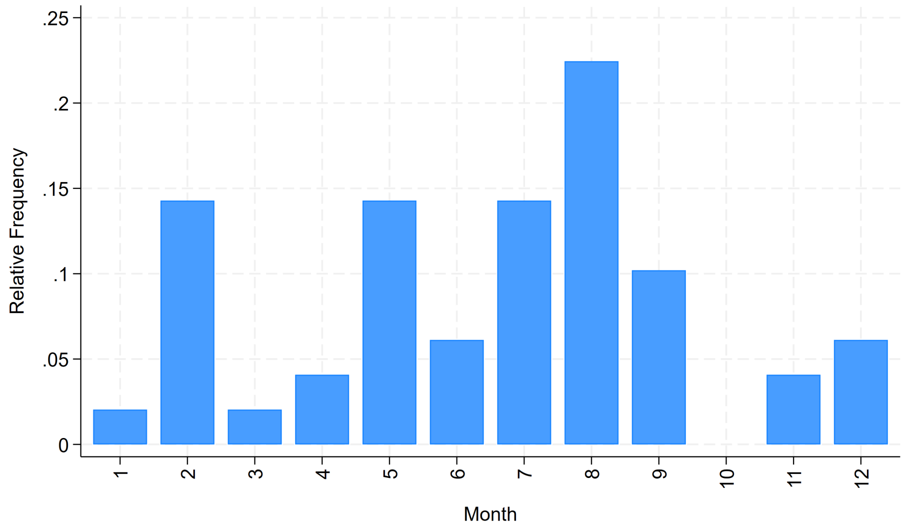

Figure 3.6: 995 Customers Annual Peaks by Month

a month. As shown in Figure 3.6, the 995 customers' annual peaks can occur during both summer and winter. In contrast, the 996 customers tend to have their annual peaks in the summer.

Figure 3.8 presents the relative frequency of daily maximum demand occurring at each hour. As shown, the system maximum demand tends to peak at 4 PM and 5 PM. In contrast, as shown in Figures 3.9 and 3.10, both 995 and 996 customers tend to peak during the midday hours.

In summary, there appears to be a relatively low or moderate degree of correlation between the maximum demand of the system and the maximum demand specific to the customer. Therefore, MDCs are less efficient in reducing system maximum demand if they primarily target customer-specific maximum demand in Alberta.

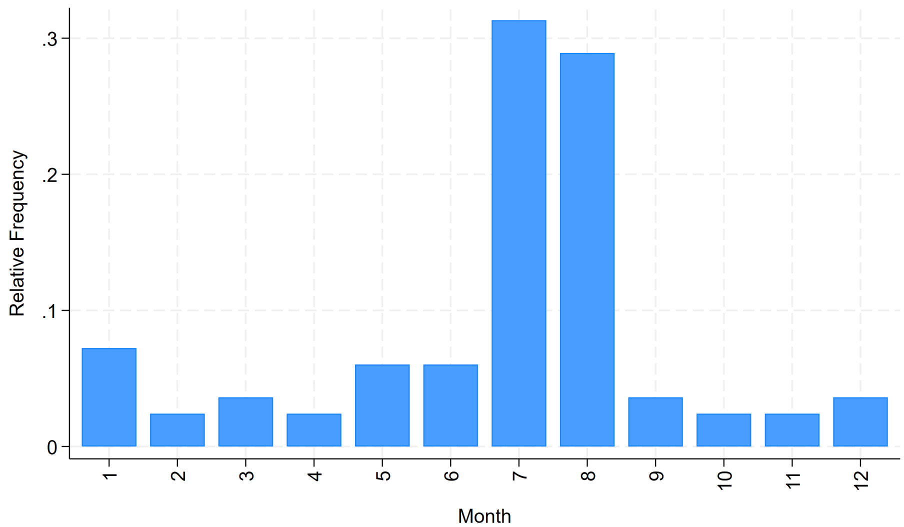

Figure 3.7: 996 Customers Annual Peaks by Month

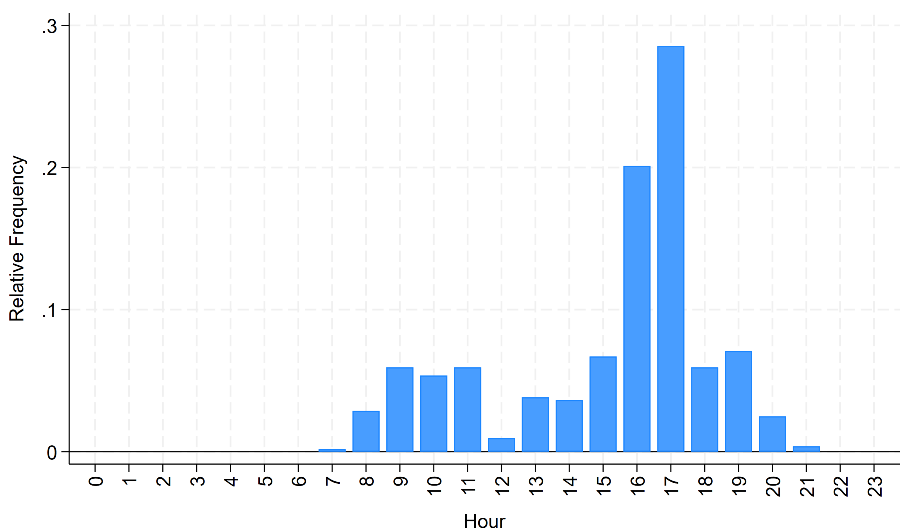

Figure 3.8: Daily System Peaks by Hour

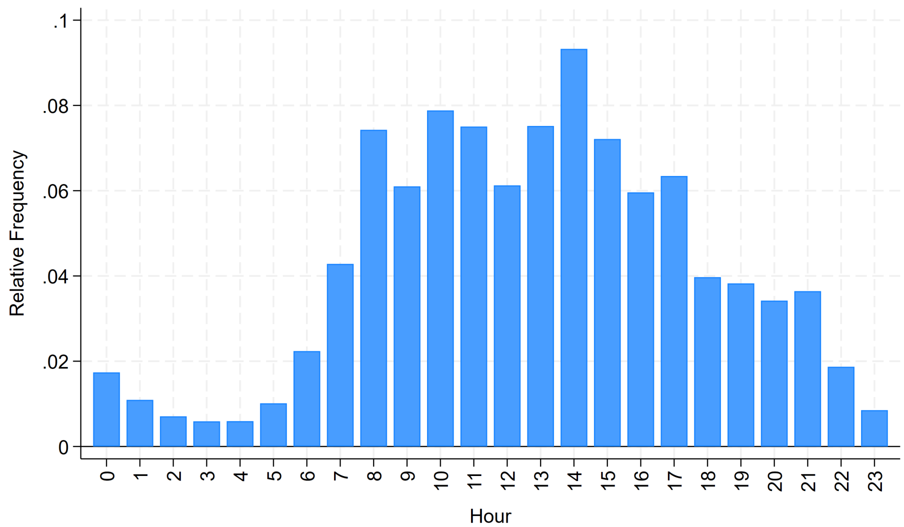

Figure 3.9: 995 Customers Daily Peaks by Hour

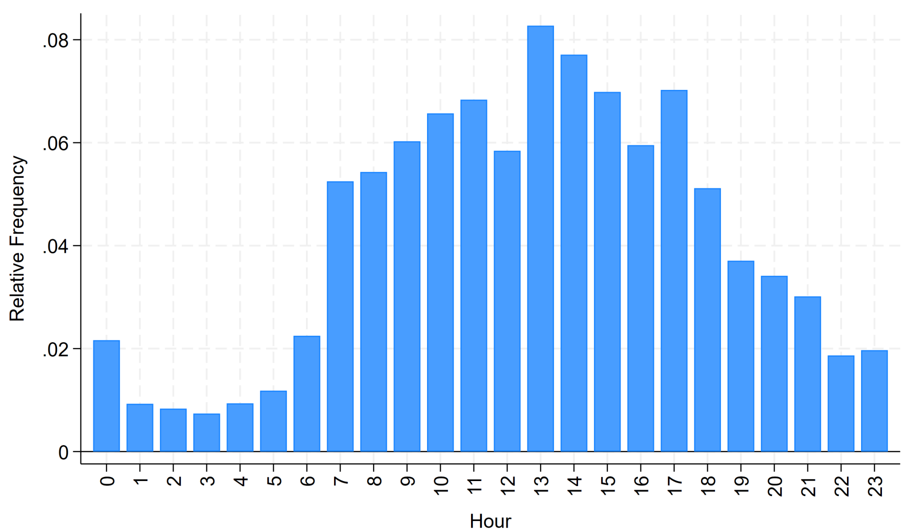

Figure 3.10: 996 Customers Daily Peaks by Hour

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