Essays on Energy and Natural Resource Economics

By

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I dedicate my dissertation to my lovely wife Yeana.

Thank you for all of your unconditional support along the way.

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Abstract

Essays on Energy and Natural Resource Economics

This dissertation consists of two essays on how residential consumers respond to a range of different electricity price structures and one on the supply side of the energy sector.

The first essay examines what information households respond to in their monthly energy bills and the implications of their behavioral responses to electricity pricing. Previous work has uncovered evidence that households largely respond to the average price they pay for energy in the previous billing period. In this essay, I re-examine whether households indeed pay attention solely to the average price. Using detailed hourly consumption data from over 100,000 households in Sacramento, California, I measure the impact of surpassing the first threshold of nonlinear tariff structures in a billing month on households' average daily electricity consumption in subsequent months. My empirical results illustrate that households that consumed enough to be subjected to a higher marginal price in the previous billing period reduced their electricity consumption in the succeeding billing month. This finding illustrates one of the many inefficiencies that arise from tiered rate structures: households' response to prices that are not reflecting current supply conditions but rather the household's past consumption levels.

The second essay studies how households respond to Time-Of-Use (TOU) electricity prices that vary throughout the course of the day. The primary purpose of the time-varying pricing scheme is to reshape households' electricity consumption in and near peak-demand hours—more specifically, to reduce their consumption during peak hours and shift some of their consumption to off-peak hours. The existing literature presents evidence that under TOU tariff structures, residential consumers reduced their electricity consumption during peak price periods, but these reductions were insensitive to the marginal changes in peak-hour prices. In this essay, I re-examine the impact of TOU rates but with a different strategy. Rather than estimating how aggregate consumption responds to TOU rates, I decompose household electricity consumption into two distinct categories: consumption for non-temperature-control and temperature-control uses. My empirical analysis shows that households indeed responded to the magnitude of the price increase in the peak rate period; however, the response was not the same for the two consumption categories. In particular, while non-temperature-control-driven consumption during

the peak hours markedly fell as the peak price increased, temperature-control-driven consumption fell prior to the peak hours, and actually increased during the peak hours, relative to the reduction in pre-peak hours, as the peak price increased. Ultimately, the differences in the responses across these two channels masked households' high price sensitivity. This also illustrates that the two types of electricity consumption evolved differently, and nonlinearly, according to daily heating degree days and the point electricity was consumed in time. These findings suggest that adopting autonomous heating control systems or augmenting additional across-day flexibility to the typical structure of TOU electricity pricing is required to maximize the benefits of the pricing scheme.

The third essay develops a discrete choice dynamic programming (DCDP) framework in continuous time by formulating fracking firms' drilling decisions as an optimal stopping problem. In a recent paper, Hotelling's classic model of nonrenewable resource extraction is recast as a drilling problem to explain observations in Texas that drilling activity responds to oil prices sensitively, while oil production from existing wells does not respond. The model in this prior paper, however, cannot rationalize the empirical phenomenon that firms in North Dakota drilled wells in both low- and high-quality locations. The DCDP model uses cost shocks to rationalize the simultaneous drilling of resources with heterogeneous quality. Further, the model can be estimated empirically using microeconomic data and also solved analytically for an aggregate solution. In the limit, the model converges to the classic Hotelling model.

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Chapter 1

Dynamic Consumption Behavior with the Lagged Price Signals

1.1 Introduction

Increasing-Block Pricing (IBP) is one of the most common electricity rate plans.[1] Under the pricing scheme, the marginal price increases, in a nonlinear way, with the customer's usage. Specifically, the price consumers pay for their marginal electricity consumption is a step function of their aggregate consumption in a billing cycle.

Economists have studied how residential consumers respond to nonlinear electricity pricing. Ito (2014) demonstrates that when faced with IBP, households respond to average prices rather than marginal prices. More recently, Shaffer (2020) shows that not all households uniformly respond to average prices. To be specific, this paper exhibits that most residential consumers respond to average prices, but their response can be veiled by the response of a small number of households mistakenly applying the marginal price to all inframarginal units of consumption, not the last unit. And in both papers, it is stressed that households' misunderstanding of nonlinear electricity pricing leads to their inefficient electricity consumption, such as over- or under-consumption.

Electricity bills, usually issued every month, have been a primary, perhaps for some households the only, source of information about their electricity consumption (e.g., the total charges, the amount of consumption, and the marginal price). Inherently, the consumption-relevant information on a monthly electricity statement is not up to date—a statement principally includes

[1] As of the end of December 2022, about 40% of the residential consumers of Pacific Gas and Electric Company (PG&E), which is one of the largest utilities in California, were on the IBP.

information about the previous billing cycle. Household electricity consumption, however, is affected, at least partly, by the intermittent bills. As illustrated in Gilbert and Graff Zivin (2014), households change their consumption behavior after receiving a monthly bill. And in addition to the key finding discussed above, Ito (2014) presents convincing evidence that households respond more to lagged average prices, which are available in monthly electricity statements, than contemporaneous ones.

There are two issues when residential consumers change their electricity consumption according to price signals delivered through monthly electricity bills. The first issue is that they respond to the incorrect prices. Whatever households' perceived price of nonlinear price schedules is, the price signals are false because these signals reflect not their contemporaneous consumption level but their past one. And households' exaggerated responses to the price signals are the second issue. Suppose that residential consumers adjust their electricity consumption according to the lagged prices. In that case, the behavioral change implies that all consumption in a billing cycle is subject to the previous billing cycle's prices. Importantly, such an implication is analogous with households' over-responses to the (current) marginal price discussed in Shaffer (2020).

On both those fronts, this paper examines households' responses to the marginal price again. For residential consumers under IBP, I measure how much electricity consumption they reduced in a billing month in response to the discontinuous increase in the marginal price at the lower base usage quantity in the immediately preceding billing month, which was not accompanied by any discontinuous change in average prices. In other words, focusing on two consecutive billing cycles, I investigate how households responded to the sharp increase in the *lagged* marginal price signaled through their monthly electricity bills.

To estimate the impact of the change in the marginal price due to surpassing a base usage quantity in a billing cycle on household electricity consumption in the following billing cycle, I adopt a Regression Discontinuity (RD) approach that exploits the sharp discontinuity in the marginal price at the threshold. Under IBP, a household's (within-billing-cycle) aggregate electricity consumption at some point completely determines the price the household pays for the marginal unit of consumption at that point. Under the known-to-consumer price determination mechanism, my identification relies on the assumption that households cannot manipulate whether they fall on one side of the cutoff or the other conditional on their monthly consumption being close to the cutoff point. In my empirical setting, the assumption is convincing for two reasons. First of all, the households in my sample had no practical way to know how much electricity they had consumed from the first day of a billing cycle to the point of marginal electricity consumption, especially before installing smart meters. They were able to find out whether their total consumption in a billing cycle surpassed the threshold only after receiving their monthly bills at the beginning of the subsequent billing cycle. On top of that, it is not feasible for them to adjust their electricity consumption precisely to avoid crossing the cutoff point due to their indispensable consumption (e.g., consumption for refrigerators and lighting) and too high information cost imposed when micromanaging electricity demand according to the change of outdoor conditions. Thus, the two points demonstrate that my RD design clearly satisfies the fundamental assumption required for identification: around the threshold, the treatment assignment is random.

Implementing the RD design to monthly billing records from hundreds of thousands of residential consumers in Sacramento, CA, I find households' interesting behavioral change with respect to electricity consumption: around the lower base usage quantity, the households that were subject to a higher marginal price because their aggregate electricity consumption in a billing month exceeded the cutoff point reduced their average daily electricity consumption by about 0.16% in the following billing month, compared to the households experiencing no change in the marginal price. Because only the marginal price discontinuously increased, not the average price, at the threshold, this result is convincing evidence that households, conservatively at least some of them, respond to marginal prices. In line with Shaffer (2020), if the identified reduction in household electricity consumption is entirely attributable to behavioral changes of a subset of residential consumers, my estimates imply that approximately 11% of households in my sample reacted to the discontinuous jump in the marginal price. More importantly, the result suggests other inefficiencies stemming from households' responses to nonlinear electricity pricing: 1) households also respond to the lagged marginal price, which is irrelevant to their present consumption level; and 2) the lagged marginal price is applied to all units of electricity consumption, not the last unit, during a billing cycle.

I also examine the heterogeneity in household responsiveness to the lagged marginal price across rate codes and seasons. In addition, my investigation of the multi-period impact of the discontinuous increase in the lagged marginal price on household electricity consumption shows whether households' use of electric heating drove the impact.

The rest of this paper proceeds as follows. In Section 2, I discuss my empirical approach and data. Section 3 presents the results from my empirical analysis. Section 4 describes the policy implications of my key findings, and Section 5 concludes.

1.2 Data and Research Design

This section provides a detailed description of the data utilized for my empirical analysis. Furthermore, this section demonstrates a key feature of my research design.

1.2.1 Background of Residential Rates of Sacramento Municipal Utility District

Sacramento Municipal Utility District (SMUD), which is the nation's sixth-largest community-owned electric utility, provides electricity to most of Sacramento County and small portions of adjoining Placer and Yolo Counties.[2]

Before the default residential rate switched to the Time-Of-Day (TOD) rate, most SMUD residential customers chose residential rates having an increasing nonlinear block-tier structure.[3] The three most popular rates for SMUD residential customers were Standard General Service (RSGH), Standard Closed Electric-Heated Service (RSCH), and Standard Open Electric-Heated Service (RSEH).[4] For those residential rates, the marginal price of the energy charge was a step function of monthly consumption relative to a base usage quantity per month, which varies seasonally. Figure 1.1 illustrates variations in price and base usage quantity over time. Two points are noteworthy from this figure: first, both tier rates and base usage quantities of the energy charges showed substantial seasonality; second, the structure of the residential rates changed from three-tier to two-tier since September 2009.

In addition to the variable charge (i.e., the energy charge), households choosing one of the three rates should pay a per-month fixed charge, called the System Infrastructure Fixed Charge. As shown in Figure A.1, the unit price of the fixed charge significantly increased between 2009 and 2014.

[2] According to the company information presented on SMUD's website, the size of this utility's service area is about 900 square miles.

[3] In my sample, only 5% of residential customers adopted the TOD rate, although SMUD already offered it.

[4] Specifically, more than 75% of SMUD residential customers in my dataset chose the RSGH rate, whereas 2% and 20% of households in my dataset adopted the RSCH and RSEH rates, respectively.

Figure 1.1: Tier Rates and Base Usage Quantities of SMUD Residential Rates

Note: The figure illustrates how SMUD changed tier rates and base usage quantities of the three major residential rate plans (i.e., RSCH, RSEH, and RSGH) over time. Both tier rates and base usage quantities show significant seasonality. The two rate plans for electric-heating households (i.e., RSCH and RSEH) had the same base usage quantities. There have been only two tiers since September 2009.

1.2.2 Data and Summary Statistics

From SMUD, I obtain household-level monthly billing history of residential consumers in the Sacramento area from 2004 to 2013. For each monthly record, account ID, premise ID, rate code, billing start and end dates, monthly consumption with its breakdown into each tier, monthly fixed charge, monthly variable charge only for kWh usage, total monthly bill, and an indicator related to solar adoption are included in the data. Of note, in my empirical analysis, I assume that a pair of account and premise IDs corresponds to an individual household. And because the monthly billing data contain no price and base usage quantity information, I append historical

Table 1.1: Summary Statistics

Bandwidth	Households	Observations	Control		Treatment	
			Mean	(S.D.)	Mean	(S.D.)
Normalized Electricity Consumption in Period 0 (%)						
5%	286,671	1,186,630	−2.454	1.444	2.485	1.407
10%	318,880	2,378,864	−4.993	2.885	4.918	2.847
15%	331,605	3,566,318	−7.543	4.324	7.357	4.322
20%	338,470	4,702,081	−10.085	5.756	9.617	5.718
25%	343,139	5,816,854	−12.612	7.184	11.870	7.144
30%	341,917	6,276,579	−15.054	8.597	14.063	8.559
Average Daily Electricity Consumption in Period 1 (kWh/Day)						
5%	286,671	1,186,630	24.329	7.922	25.296	8.143
10%	318,880	2,378,864	23.776	7.786	25.782	8.290
15%	331,605	3,566,318	23.231	7.674	26.270	8.450
20%	338,470	4,702,081	22.681	7.582	26.744	8.624
25%	343,139	5,816,854	22.140	7.509	27.202	8.805
30%	341,917	6,276,579	20.674	6.560	26.517	7.874

Note: This table presents summary statistics for household electricity consumption. Including this table, all following tables are generated using the *stargazer* package for *R* (Hlavac, 2022).

price schedules and base usage quantities presented by SMUD. Unfortunately, my monthly billing data also lack any socioeconomic and demographic information.

For my empirical analysis throughout this paper, I construct a sample from the monthly billing data for SMUD residential customers. My sample satisfies the following criteria. First, I focus on households that consistently used one of the three major residential rates (i.e., RSGH, RSCH, and RSEH) in their billing history. Second, I only utilize pre-2010 billing records to rule out the potential undermining of the validity of my identification assumption, which will be discussed in a later section. Third, I focus on households whose number of billing periods is greater than or equal to 24. Fourth, I focus on SMUD residential customers with reliable billing records only.[5] Fifth, my sample only includes households that crossed the lower threshold

[5] To be specific, I exclude, from the sample used for my empirical analysis, households that have billing records being applied to any of the following conditions: 1) observations whose length of the billing period is either less than 27 or greater than 34; 2) observations with negative values for either quantities or charges; 3) observations

at least once in their billing history.[6] The procedure results in 16,322,353 billing records for 365,975 households. Table 1.1 provides summary statistics for my sample. Furthermore, Figure A.2 shows, for each rate code, households' average daily electricity consumption by month of the year.

To take account of the impact of weather conditions, especially outdoor temperatures, on household electricity consumption, I utilize the Local Climatological Data (LCD) for the Sacramento International Airport, published by the National Oceanic and Atmospheric Administration (NOAA). Using daily heating degree days (HDDs) and daily cooling degree days (CDDs) in the LCD between 2004 and 2009, I calculate each monthly billing period's accumulated HDDs and CDDs, which are used to compute the average daily HDDs and CDDs.

1.2.3 Research Design

1.2.3.1 Monthly Bill as the Only Source of Electric Usage Information for Households

Before 2009, there was no feasible way for SMUD residential customers to access real-time information related to their electricity use. SMUD initiated installations of smart meters, allowing its residential and business customers to view their electricity usage online when they want, in late 2009. The electric service completed it in the first quarter of 2012. Also, the three types of bill alert SMUD are offering were introduced in 2017.[7] Therefore, for households using SMUD-delivering electricity, the only practical source of information about their electricity consumption had been their monthly bill statements, which send out (either e-mail or U.S. mail) after 3 or 4 business days from the last day of each billing cycle.

The issue of households' welfare losses due to their response to discontinuous changes in the lagged marginal price suggests the importance of providing seemly price information in an appropriate manner. Many studies about various time-varying electricity pricing show that households changed their consumption behavior in response to the information about consump-

having overlapping billing periods within a pair of account and premise IDs; and 4) the length of the period between two consecutive billing months was greater than 14 at least once.

[6] In other words, I drop always-light- and always-heavy-users from my sample.

[7] SMUD provides its customers with three types of bill alerts, via text or e-mail, as a billing service: 1) Mid-Bill Alerts send an alert on the 16th day of a customer's billing period and advise what his usage has been and what the cost is as of that day, 2) High Bill Alters compare a customer's current billing cycle to the same billing cycle in the previous year and alerts the customer if their current usage is running higher than before, and 3) Bill Threshold allows a customer to know when his bill has reached a certain amount set in advance by himself.

tion and prices (Faruqui and Sergici, 2011; Jessoe and Rapson, 2014; Pon, 2017; Bollinger and Hartmann, 2020). My empirical finding demonstrates that even under IBP, such information, though lagged, still plays a role in household electricity consumption. In this respect, providing household-specific as well as current price information for residential consumers, via text messages or app notifications regularly, could encourage them to respond to *true* price signals rather than lagged ones, which in turn avoid the negative impact on household welfare. Based on the dissipating effect of intermittently salient information discussed in Gilbert and Graff Zivin (2014), a high frequency of informing the latest tailored price information might maximize households' behavior change in electricity consumption. In addition, because sending such information-bearing notifications is available at a very low cost these days, this type of information provision would be a practical policy instrument for utilities, especially in developing countries where the transition toward dynamic electricity pricing is difficult due to substantial investments in installing smart metering systems.

1.2.3.2 Regression Discontinuity Design

In this paper, I employ a Regression Discontinuity (RD) design to examine how households' electricity consumption responds to the marginal price informed via monthly energy statements under Increasing-Block Pricing (IBP). In previous studies, a common challenge in measuring consumption responses to price changes has been discussed repeatedly: constructing a well-defined control group is difficult due to that consumers typically experience the same price variation. However, the setting I exploit in this paper enables me to address the identification challenge.

The RD design I implement in this paper relies on three points. First, the marginal price is a step function of consumption level in the increasing block-tier rate plans chosen by SMUD residential customers. That is, under IBP, the price a household pays for the marginal electricity consumption increases discontinuously at some pre-determined aggregate consumption in a billing cycle. Second, as discussed in Section 1.2.3.1, before 2009, SMUD residential customers had practically no way to know the marginal price in a billing cycle within the very cycle. They were informed of the price they paid for the marginal electricity consumption in a billing cycle only through their electricity bills delivered in the following cycle. Third, it is not generally feasible for households to consume only a pre-targeted amount of electricity within a billing cycle. In general, households have limited capability to control their electricity consumption due to the minimal essential demand (e.g., usage for refrigerators and lighting). In addition, because household electricity consumption heavily depends on outdoor temperature variation, managing one's own electricity usage not to exceed the target amount of electricity consumption could incur too high information cost, which might result in rational inattention (Sallee, 2014), even if households are available to adjust their consumption behavior with complete flexibility.

Regarding the first point, the discontinuities under the nonlinear electricity schedules allow utilizing a RD design. In my RD design, the running variable is the level of electricity consumption in a household during a billing period (denoted as Period 0), whereas the outcome variable corresponds to the household's average daily electricity consumption during the subsequent billing period (denoted as Period 1). So, in this quasi-experimental setting, I compare SMUD residential customers just above and below the thresholds of the tier rates, called base usage quantities. Under IBP, surpassing a threshold leads to an increase in the marginal price households pay for electricity consumption mechanically. Here, the discontinuous increase in the marginal price, which accompanies *no discontinuous change in the average price*, applies only to Period 0, not to Period 1.[8] Moreover, information about whether households were subject to a higher marginal price in a billing period is delivered early in the subsequent billing period through their monthly electricity bills. Therefore, any changes with respect to the electricity consumption of households just above the threshold (i.e., households in the treatment group) in Period 1, compared to households just below the threshold (i.e., households in the control group), can be understood as their short-term behavioral responses stemming from the sharp jump in the marginal price in Period 0. Figure 1.2, showing how the mean of households' average daily electricity consumption in Period 1 evolves around the lower base usage quantity, seems to indicate the existence of such behavioral responses.

The last two points demonstrate that the fundamental identifying assumption of the RD design is reasonable. The fundamental identifying assumption is that SMUD residential customers just below a base usage quantity are expected to be very similar to those just above it, along with observed and unobserved characteristics. In other words, a group of households in the small neighborhood of the threshold is not different from one obtained from a randomized experiment. In my setting for empirical analysis, SMUD residential customers were unable to be aware of how far away they were from a given cutoff point in real time. Furthermore, as discussed above,

[8] The average price smoothly grows around the cutoff point.

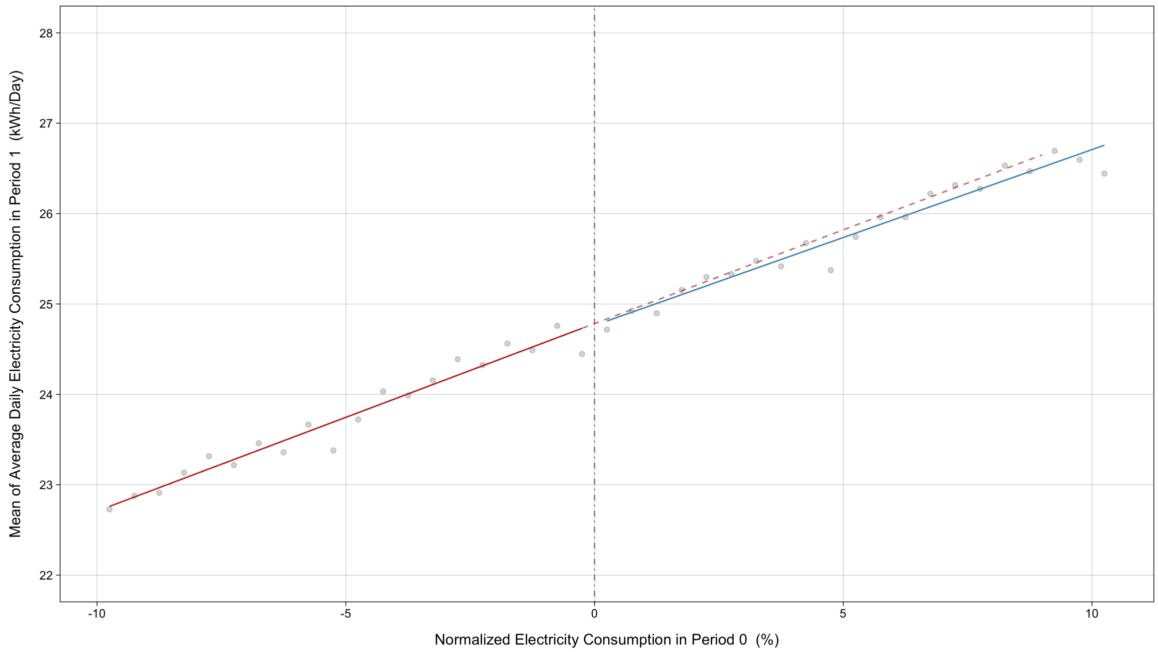

Figure 1.2: Mean of Average Daily Electricity Consumption in Period 1 over $\overline{NC}_0$

Note: This figure's scatter points correspond to the average daily electricity consumption in Period 1, computed by bins with a bandwidth of 1% of $\overline{NC}_0$. The solid line on each side of the vertical dot-dash line is a parametric fit obtained from the regression of the average daily electricity consumption on $\overline{NC}_0$. The dashed red line is an extension of the solid red line. The gap between the dashed red and solid blue lines seems to indicate a non-negligible treatment effect.

it is not convincing that they can perfectly control their electricity consumption during a billing cycle to use exactly a target amount of electricity by the end of the last day of the billing cycle. Hence, it is highly unlikely that the customers precisely adjusted their consumption behavior so as to avoid surpassing the cutoff point, which in turn prevented them from leading to a higher marginal price. That is, it seems plausible that households were not able to sort themselves around the threshold strategically. Therefore, any discontinuity gap in the outcome variable can be attributed to the discontinuous increase in the marginal price at the threshold in Period 0.

1.2.3.3 The Validity of the Regression Discontinuity Design

Two pieces of evidence support the assumption that base usage quantities do not correspond to jumps in household characteristics. First, as illustrated in Figure 1.3, each density plot of the running variable is very smooth, without any bump (i.e., excess mass), around base usage quantities at which marginal prices jump. The set of density plots that show apparent continuity at the thresholds suggests households' inability to precisely adjust their electricity consumption

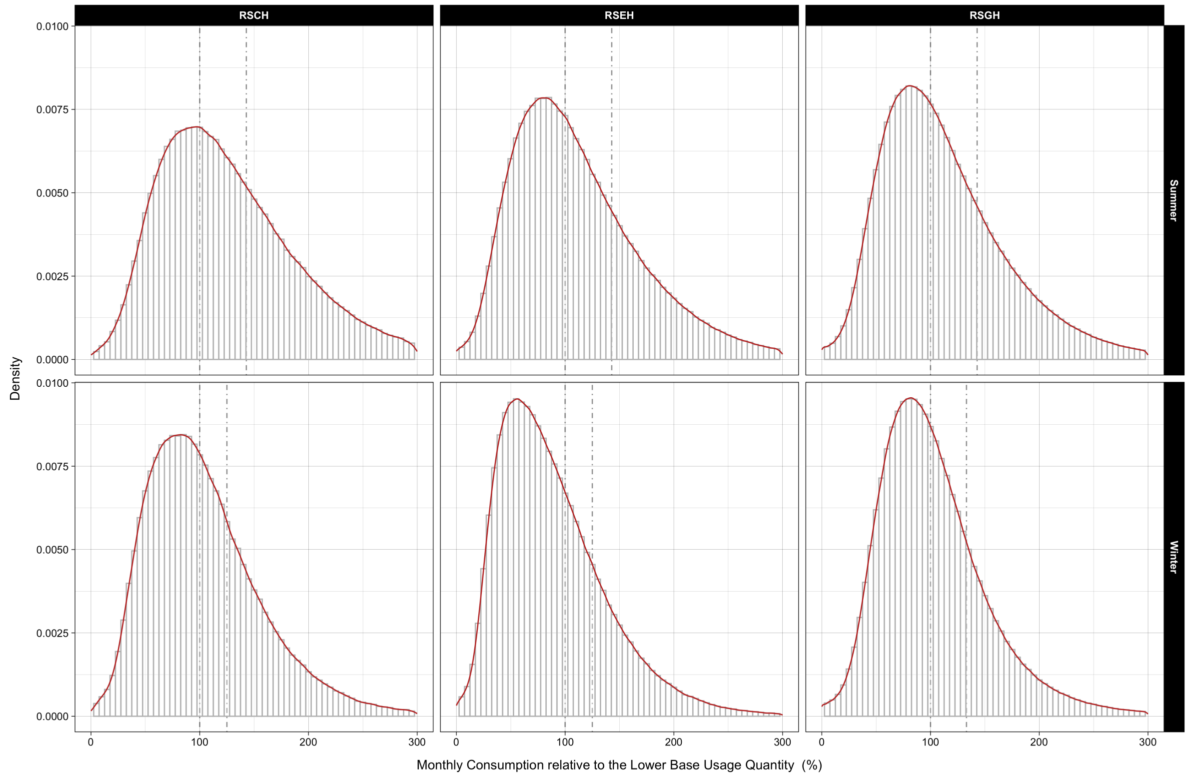

Figure 1.3: Distribution of Electricity Consumption by SMUD Residential Customers

Note: This figure presents histograms, with kernel density estimates, for electricity consumption by SMUD residential customers. Each of the six panels in the figure is for a pair of three major residential rates (i.e., RSCH, RSEH, and RSGH) and two seasons (i.e., summer and winter). Dot-dashed vertical lines in each panel are base usage quantities for the corresponding rate code and season.

in order not to be subject to a higher marginal price.

Second, Figure 1.4 demonstrates that households' average daily electricity consumption during Period 0 evolved smoothly around the lower cutoff point. This figure allows me, at a minimum, not to reject the assumption of local randomization around the base usage quantity, even though examining an observed covariate around the thresholds is not also a direct test for the validity of the assumption.

1.3 Empirical Analysis and Results

1.3.1 Household Responses to the Lagged Marginal Prices

1.3.1.1 Econometric Model

Exploiting the sharp Regression Discontinuity (RD) design described earlier, I estimate the following econometric specification to measure how SMUD residential customers respond, in

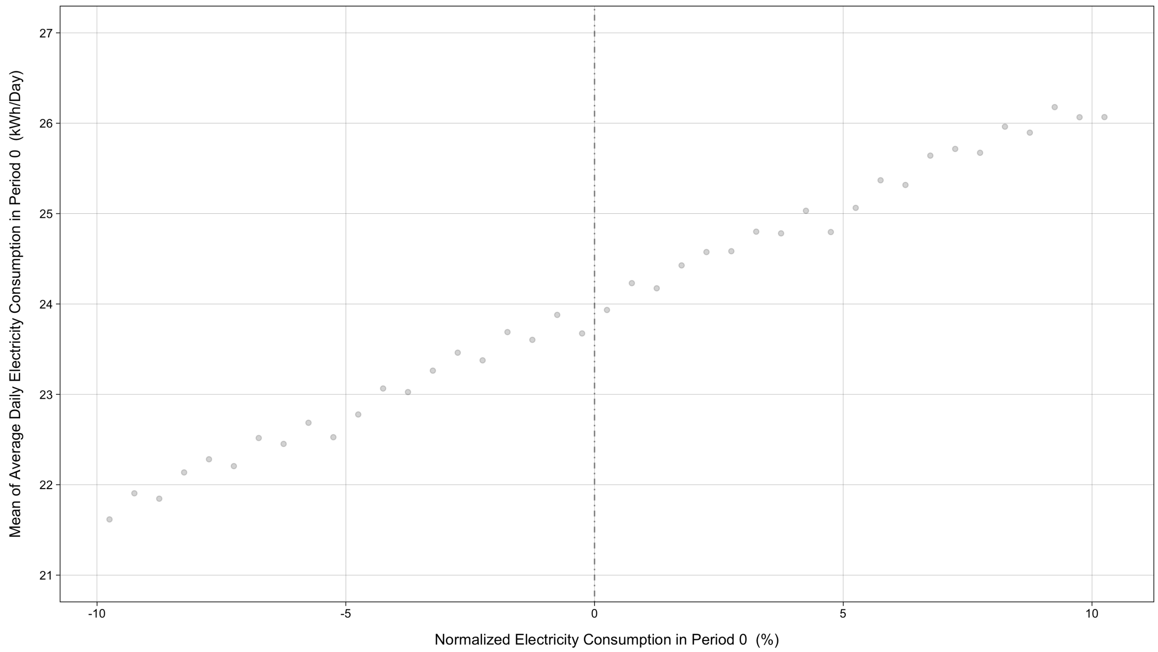

Figure 1.4: Mean of Average Daily Electricity Consumption in Period 0 over $\overline{NC}_0$

Note: In this figure, the scatter points correspond to the average daily electricity consumption in Period 0, calculated by binds with a bandwidth of 1% of $\overline{NC}_0$. As can be seen, the average daily electricity consumption evolves smoothly around the cutoff point (i.e., $\overline{NC}_0 = 0$).

terms of their electricity consumption in a billing month (i.e., Period 1), to the discontinuous change in the marginal prices due to exceeding the lower base usage quantity in the previous billing month (i.e., Period 0):

$$ADC_{i,1} \;=\; \beta\,\mathbb{1}[Treatment]_{i,0} \;+\; f\left(\overline{NC}_{i,0}\right) \;+\; \boldsymbol{X'\alpha} \;+\; \delta_{ym} \;+\; \epsilon_{i,1} \tag{1.1}$$

The dependent variable $ADC_{i,1}$ is the average daily consumption by household i in Period 1. $\overline{NC}_{i,0}$ corresponds to the running variable, household i's normalized consumption in Period 0:

$$\overline{NC}_{i,0} \;=\; kWh_{i,0} \;-\; BUQ_{i,0} \tag{1.2}$$

where $kWh_{i,0}$ and $BUQ_{i,0}$ are, in Period 0, household i's aggregate electricity consumption and the lower base usage quantity, respectively. The binary indicator variable $\mathbb{1}[Treatment]_{i,0}$ is equal to 1 only if household i's aggregate electricity consumption in Period 0 exceeded the lower base usage quantity:

$$\mathbb{1}[Treatment]_{i,0} \;=\; \begin{cases} 0 & \text{if } \overline{NC}_{i,0} \;\leqslant\; 0 \\ 1 & \text{if } \overline{NC}_{i,0} \;>\; 0 \end{cases} \tag{1.3}$$

For $f\left(\overline{NC}_{i,0}\right)$, which is a continuous function of $\overline{NC}_{i,0}$, I utilize a variety of functional forms to show the robustness of my estimates. $\boldsymbol{X}$ are covariates, such as average daily Cooling Degree Days (CDDs) and average daily Heating Degree Days (HDDs). δ_{ym} is billing year-by-month fixed effects (FEs).[9] The last term $\epsilon_{i,0}$ is a stochastic error term. In this model, the coefficient of interest β captures the treatment effect. I cluster the standard errors at the household ID as well as billing year-by-month levels to allow correlations across households in a given month.

In the specification, each household's average daily electricity consumption, instead of the aggregate consumption, in a billing cycle is utilized as the dependent variable. My sample contains household-level monthly billing records. But because of the fact that each billing month consists of a different number of days, I use each billing month's average daily consumption for my empirical analysis. For the same reason, average daily CDDs and HDDs are exploited in later analysis.

1.3.1.2 Regression Discontinuity Results

Table 1.2 summarizes the regression results of several alternate specifications for the bandwidth of 10%. Column (1) reports estimates from the most straightforward RD specification, controlling linearly for $\overline{NC}_{i,0}$, without any control and FEs. Column (2) adds controls for households' cooling and heating needs, significantly driving household electricity consumption. In addition to those two controls, column (3) uses billing year-by-month FEs. Adding the FEs attenuates the estimate of interest. Moreover, the standard errors of the estimated treatment effect are substantially smaller, suggesting that controlling for time-varying factors is important.[10] In this specification, the estimated treatment effect indicates a discontinuous reduction in households' electricity demand by 0.040 kWh, which amounts to 0.16% of their average daily electricity consumption. This estimate is statistically different from 0 at the 5% level. Columns from (4) to (6) additionally include the interaction term between the binary indicator and the running variable. Adding the interaction term to the specifications has only minimal impact on estimates.

The identified reduction in household electricity consumption provides strong evidence that households respond to lagged marginal prices. As discussed in Section 1.2.3.2, the discontinuous increase in the marginal price at the lower base usage quantity was not followed by any discontinuous change in the average price. Moreover, the households in my sample were able to

[9]For a given billing observation, the mid-date of the observation determines the billing month-by-year.

[10]Table A.2 shows the RD estimates of the treatment effect from specifications without the billing year-by-month FEs. From this table, it is convincing that including the FEs is necessary to reduce sampling variance.

Table 1.2: Regression Discontinuity Results

	Dependent Variable					
	Average Daily Electricity Consumption (kWh/Day)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$[Treatment]	−0.047*	−0.054*	−0.040**	−0.047*	−0.054*	−0.038**
	(0.027)	(0.030)	(0.018)	(0.027)	(0.030)	(0.018)
NC0	0.207***	0.197***	0.219***	0.207***	0.197***	0.222***
	(0.007)	(0.006)	(0.005)	(0.007)	(0.007)	(0.005)
$\mathbb{1}$[Treatment] × NC0				0.0002	0.001	−0.006
				(0.004)	(0.004)	(0.004)
Average Daily CDDs		0.753***	1.146***		0.753***	1.146***
		(0.121)	(0.106)		(0.121)	(0.106)
Average Daily HDDs		0.281***	0.428***		0.281***	0.428***
		(0.078)	(0.106)		(0.078)	(0.106)
(Constant)	24.810***	19.974***		24.810***	19.973***	
	(0.542)	(0.941)		(0.542)	(0.941)	
Bandwidth	10%	10%	10%	10%	10%	10%
FEs: Billing Year-by-Month	No	No	Yes	No	No	Yes
Observations	2,378,864	2,378,864	2,378,864	2,378,864	2,378,864	2,378,864
Adjusted R^2	0.021	0.120	0.293	0.021	0.120	0.293

Note: The table shows, for the bandwidth of 10%, the regression results from different econometric specifications. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

notice the price jump only through their monthly bill statements, which were delivered a few days after the first day of the new billing month. Collectively, my estimates reveal an inefficiency stemming from households' responses to nonlinear electricity pricing because the lagged marginal price reflects their consumption history, not their contemporaneous consumption. In other words, under IBP, the untimely price signals drive, at least partly, households' electricity consumption.

Importantly, the estimated discontinuous decrease in residential electricity consumption also suggests that SMUD residential customers overreacted to the lagged marginal price under non-linear electricity pricing. The discontinuous change in the marginal price at the lower base usage quantity occurred in a billing cycle (i.e., in Period 0). And my estimates show that in the following billing cycle (i.e., in Period 1), the customers reduced their electricity consumption as a response to the price variation. Consequently, the sharp increase in the marginal price at the cutoff point in Period 0 affected all consumption, not the marginal one, in Period 1. That is, households excessively applied the lagged marginal price to every unit of electricity consumption during a billing month.

Inspired by Shaffer (2020), the estimates could be interpreted differently. The paper finds that a subgroup of less than 10% of households, which applies the marginal price to all consumption, was driving the seemingly overall response, in which the primary response to the average price is masked. If this is also true in my setting, then the measured decrease in household electricity consumption would be attributed to a subset of my sample. Suppose that there are two distinct types of SMUD residential customers: households over-responding to the lagged marginal price and those not responding to it.[11] My back-of-the-envelope calculation suggests that about 11% of over-responders produce the estimated treatment effect.[12] The share of over-responding households is obtained from the following steps: 1) computing the price elasticity of household electricity consumption by using the estimated treatment effect (i.e., the measured reduction in households' average daily electricity consumption), the average daily electricity consumption, the size of the price jump at the lower base usage quantity, and the average price at the cutoff point; and then 2) for a given price elasticity, which is available from other papers or reports, estimating how much households would have to respond to the lagged marginal price to obtain the price elasticity implied by my RD estimate. Moreover, for this computation, I exploit billing records only from non-electric-heating households (i.e., households choosing the

[11]Here, I do not consider the type of households that respond to the average price because the change in the lagged marginal price at the threshold does not accompany any discontinuous change in the average price.

[12]To obtain the proportion of over-responding households, I exploit the following values: 1) the daily price elasticity for default non-EAPR customers (i.e., -0.030), which is presented in *Section 7.2 Price Elasticity Estimates* of Potter, George and Jimenez (2014); and 2) the treatment effect, estimated with the value of bandwidth 10%, for households selecting the RSGH rate plan (i.e., -0.060), which is given in Table A.3.

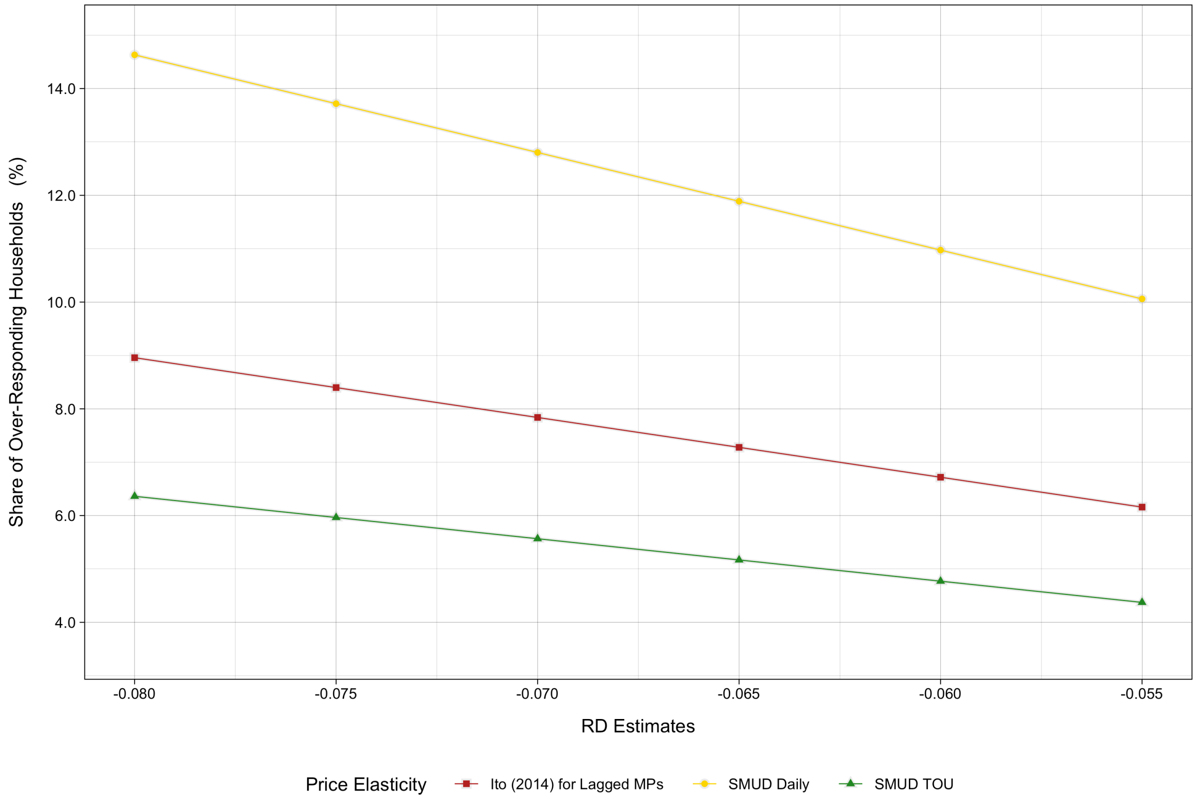

Figure 1.5: The Share of Over-Responding Households

Note: This figure shows, for different price elasticities of household electricity consumption, how the share of over-responding households varies with the value of the RD estimates. Two price elasticities for SMUD residential customers are in Potter, George and Jimenez (2014), whereas the remaining price elasticity, estimated from PG&E residential customers' billing data, is from Ito (2014). See the text for details.

RSGH rate plan.) Interestingly, my calculation, which indicates the reduction in electricity consumption by a subset of households in my sample, parallels the finding in the paper. Figure 1.5 visualizes, for different price elasticities of residential electricity consumption, how the proportion of over-responding households varies with the magnitude of the RD estimates identified.

1.3.1.3 Robustness Checks

Regression Discontinuity Results for Different Bandwidths and Functional Forms — Table 1.3 summarizes the regression results for a set of different bandwidths. The estimated treatment effect for the households in a very narrow range from the lower base usage quantity (i.e., the households within the bandwidth of 5%) is not statistically significant even at the 10% level. Except for the bandwidth of 5%, the treatment estimates range from -0.038 to -0.069 and statistically differ from zero at least at the 5% level. The estimated treatment effect is

Table 1.3: Robustness Checks: For Different Bandwidths

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$[Treatment]	−0.026	−0.038**	−0.039**	−0.064***	−0.060***	−0.061***	−0.060***	−0.069***
	(0.027)	(0.018)	(0.017)	(0.015)	(0.014)	(0.012)	(0.020)	(0.023)
NC0	0.207***	0.222***	0.224***	0.225***	0.225***	0.221***	0.236***	0.229***
	(0.009)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)	(0.009)
$\mathbb{1}$[Treatment] × NC0	0.017*	−0.006	−0.010***	−0.009***	−0.009***	−0.015***	−0.019***	−0.017***
	(0.010)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Average Daily CDDs	1.146***	1.146***	1.146***	1.146***	1.145***	1.135***	1.102***	1.133***
	(0.105)	(0.106)	(0.106)	(0.105)	(0.105)	(0.109)	(0.115)	(0.129)
Average Daily HDDs	0.427***	0.428***	0.429***	0.431***	0.433***	0.375***	0.691***	0.742***
	(0.108)	(0.106)	(0.105)	(0.104)	(0.103)	(0.128)	(0.128)	(0.202)
Bandwidth	5%	10%	15%	20%	25%	30%	35%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,186,630	2,378,864	3,566,318	4,702,081	5,816,854	6,276,579	4,093,259	3,904,120
Adjusted R^2	0.282	0.293	0.311	0.334	0.361	0.536	0.550	0.592

Note: This table shows the results of robustness checks for a range of bandwidths using the regression in the specification (6) in Table 1.2. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month. See the text for details; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

almost identical for the bandwidths of 10% and 15%. For wider bandwidths falling between 20% and 40%, the magnitude of the estimated treatment effect increases and remains stable.[13] Interestingly, this table clearly shows that the wider the bandwidth employed, the larger the estimated treatment effect. In other words, the treatment estimates approach zero as I move even closer to the lower base usage quantity.

There are several possible explanations for this monotonic trend in the treatment effect. First, it may be more difficult or demanding for SMUD residential customers near the threshold to notice, from their monthly bill statements, that their electricity consumption in the previous

[13]The number of observations increases with the size of the bandwidth exploited, except the two widest ones. The exceptions are because I drop observations crossing the higher base usage quantity to avoid picking up the effect of surpassing the higher cutoff point.

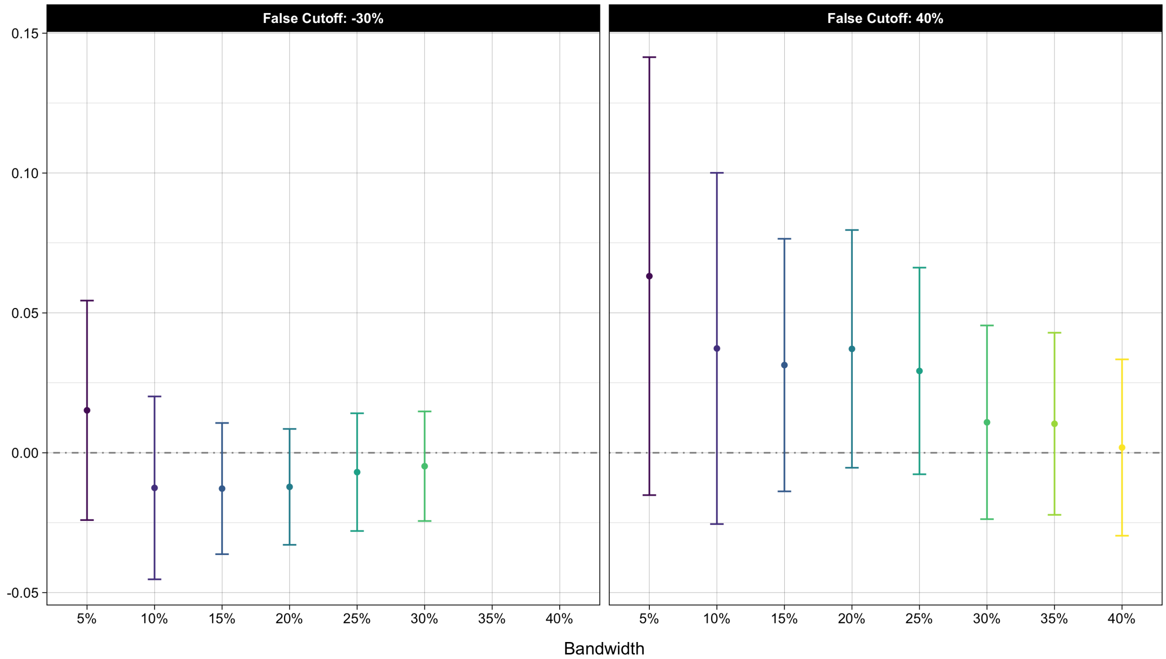

Figure 1.6: Robustness Checks: Falsification Tests

Note: This figure shows the results of falsification tests exploiting two placebo thresholds at -30% and 40% from the point $\overline{NC}_0 = 0$. As depicted, no RD estimate is statistically different from zero. See the text for details.

billing month barely exceeded the lower base usage quantity, which in turn made them experience a discontinuous increase in the marginal price. Second, households whose electricity consumption just surpassed the cutoff point in a billing cycle could intentionally ignore the lagged price signal in the subsequent billing cycle. Some of them likely understood that their immediate electricity consumption was utterly irrelevant to the signal. And it is also possible that adjusting their electricity consumption pattern against the lagged marginal price during a whole billing month led to too much cost for some treated households very near the threshold compared to its benefit. Third, households near the lower base usage quantity may respond differently to the lagged marginal price compared to those farther from the threshold. Specifically, conditional on a given magnitude of the increase in the lagged marginal price, heavy electricity consumers could be more responsive to the price signal.

Tables 1.4 and A.1 present the regression results from other specifications having different functional forms. As illustrated in Figure A.3, a linear regression function seems highly reasonable on both sides of the threshold, even for broader bandwidth. The robustness of the results from the first four columns in Table 1.4 confirms that the linear approximation of the regression

Table 1.4: Robustness Checks: For Different Functional Forms, 1st- and 2nd-Order Polynomial Models

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙[Treatment]	-0.038^{**}	-0.064^{***}	-0.061^{***}	-0.069^{***}	-0.018	-0.028	-0.068^{***}	-0.082^{***}
	(0.018)	(0.015)	(0.012)	(0.023)	(0.028)	(0.020)	(0.014)	(0.021)
NC0	0.222^{***}	0.225^{***}	0.221^{***}	0.229^{***}	0.223^{***}	0.222^{***}	0.216^{***}	0.224^{***}
	(0.005)	(0.005)	(0.006)	(0.009)	(0.011)	(0.006)	(0.006)	(0.010)
𝟙[Treatment] × NC0	-0.006	-0.009^{***}	-0.015^{***}	-0.017^{***}	-0.020	-0.013^{**}	-0.004^{**}	-0.003^{*}
	(0.004)	(0.002)	(0.002)	(0.004)	(0.014)	(0.005)	(0.002)	(0.002)
NC0^2					0.0001	-0.0002	-0.0001^{**}	-0.0001^{*}
					(0.001)	(0.0002)	(0.0001)	(0.0001)
𝟙[Treatment] × NC0^2					0.001	0.001^{***}	-0.0001	-0.0001
					(0.001)	(0.0002)	(0.0001)	(0.0001)
Average Daily CDDs	1.146^{***}	1.146^{***}	1.135^{***}	1.133^{***}	1.146^{***}	1.146^{***}	1.135^{***}	1.133^{***}
	(0.106)	(0.105)	(0.109)	(0.129)	(0.106)	(0.105)	(0.109)	(0.129)
Average Daily HDDs	0.428^{***}	0.431^{***}	0.375^{***}	0.742^{***}	0.428^{***}	0.431^{***}	0.375^{***}	0.742^{***}
	(0.106)	(0.104)	(0.128)	(0.202)	(0.106)	(0.104)	(0.128)	(0.202)
Bandwidth	10%	20%	30%	40%	10%	20%	30%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,378,864	4,702,081	6,276,579	3,904,120	2,378,864	4,702,081	6,276,579	3,904,120
Adjusted R^2	0.293	0.334	0.536	0.592	0.293	0.334	0.536	0.592

Note: This table reports the results of robustness checks for different functional forms, specifically the first- and second-order polynomial models. For each functional form, I run regressions with four different bandwidths (i.e., 10%, 20%, 30%, and 40%). Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

line does not induce considerable biases in my RD estimates. In addition, the RD estimates in the two tables suggest that for wider bandwidths, adding higher-order polynomials of the running variables is still reasonable for the estimates to be precise.

Falsification Test — Figure 1.6 summarizes the results from falsification tests that examine

Table 1.5: Heterogeneity in Household Responses: Treatment Effects by Season

	Dependent Variable								
	Average Daily Electricity Consumption (kWh/Day)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
𝟙[Treatment]	−0.129**	−0.101	−0.127	−0.127***	−0.148**	−0.052	−0.060***	−0.074**	−0.070***
	(0.064)	(0.134)	(0.082)	(0.044)	(0.062)	(0.091)	(0.016)	(0.035)	(0.015)
NC0	0.308***	0.234***	0.332***	0.283***	0.209***	0.309***	0.215***	0.208***	0.191***
	(0.012)	(0.021)	(0.016)	(0.011)	(0.010)	(0.012)	(0.006)	(0.012)	(0.003)
𝟙[Treatment] × NC0	−0.030**	−0.014	−0.043*	0.004	0.020**	−0.0004	−0.010***	−0.007	−0.006**
	(0.012)	(0.013)	(0.021)	(0.009)	(0.010)	(0.017)	(0.003)	(0.006)	(0.003)
Average Daily CDDs	0.845***	1.270***	4.291***	0.928***	1.372***	4.763***	1.172***	1.502***	1.320***
	(0.161)	(0.165)	(0.850)	(0.171)	(0.154)	(0.963)	(0.108)	(0.167)	(0.290)
Average Daily HDDs	1.212***	2.421***	0.833***	1.226***	2.283***	0.856***	0.227**	2.089***	0.037
	(0.212)	(0.218)	(0.191)	(0.213)	(0.231)	(0.230)	(0.090)	(0.243)	(0.080)
Rate Code	RSCH	RSCH	RSCH	RSEH	RSEH	RSEH	RSGH	RSGH	RSGH
Season	All	Summer	Winter	All	Summer	Winter	All	Summer	Winter
Bandwidth	10%	10%	10%	10%	10%	10%	10%	10%	10%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130,757	35,948	46,731	306,775	106,231	102,522	1,941,332	575,228	695,162
Adjusted R^2	0.535	0.414	0.259	0.571	0.418	0.301	0.486	0.540	0.167

Note: This table shows how the treatment effect varies across seasons. I run three regressions for each of the three major residential rate plans (i.e., RSCH, RSEH, and RSGH). I utilize the observations from June through September for the summer season, whereas I use the observations from December through March for the winter season. The first columns for each rate plan report the regression results exploiting all available observations. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

treatment effects at two placebo cutoff points (i.e., at −30% and 40% of the normalized electricity consumption in Period 0 from the *true* lower base usage quantity).[14] In the falsification tests, I only use bandwidths less than the distance between a false threshold and the (actual) lower base usage quantity to avoid capturing some of the treatment effect. As clearly demonstrated, no estimate is different from zero at the 5% level, suggesting that my RD design is valid.

[14]That is, the two false thresholds are at 70% and 140% of the normalized consumption in Period 0. Following the suggestion in Imbens and Lemieux (2008), I select those false cutoff points that are close to the median of the running variable on each side of the *true* cutoff point.

1.3.1.4 Heterogeneity in Household Responses to the Lagged Marginal Prices

Treatment Effects by Season — Table 1.5 summarizes how households responded differently to the lagged marginal price in different seasons. In this table, based on the billing month of Period 0, the summer season is from June to September, while the winter season is from December to March. Of note, there was no change in the lower base usage quantity during each season. For each of the three rate codes (i.e., RSCH, RSEH, and RSGH), the first columns (i.e., columns (1), (4), and (7) in the table) present the treatment effect obtained by exploiting meter readings from all months.

The two rate groups for households with electric heating (i.e., RSCH and RSEH) shared identical base usage quantities in my sample. The only difference between them was that households choosing the RSCH rate plan paid a much lower price in the winter season. Generally, households with electric heating show very similar consumption changes, though the large standard errors of the coefficient of interest make it difficult to say anything conclusive about any difference between the two rate groups.

Residential customers adopting the RSGH rate plan, which experienced relatively small seasonal changes in base usage quantities, show similar reductions in daily electricity consumption in both seasons, except that the RD estimate for the summer season demonstrates much larger standard errors.

Treatment Effects at the Higher Base Usage Quantity — Table 1.6 presents the results of applying the RD design to the higher base usage quantity. In other words, the RD estimates shown in this table demonstrate how SMUD residential customers responded to the lagged marginal price at the higher base usage quantity. Interestingly, no estimated treatment effect is statistically significant at the 5% level. In other words, the table highlights that households did not respond to the lagged marginal price at the higher base usage quantity.

There is a number of possible reasons for the empirical finding. First, considering the consumption reductions around the lower base usage quantity, this finding may indicate that households' responsiveness to the lagged marginal price varies with the level of electricity consumption. If heavy electricity consumers, presumably high-income households, tend to pay less attention to how much they are paying for their marginal electricity consumption, no response at the higher cutoff point seems reasonable. Second, no change in households' consumption behavior

Table 1.6: Heterogeneity in Household Responses: Treatment Effect at the Higher Base Usage Quantity

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$[Treatment]	0.045	−0.009	0.002	0.003	−0.007	−0.022*	−0.006	−0.011
	(0.037)	(0.028)	(0.024)	(0.022)	(0.018)	(0.012)	(0.015)	(0.018)
NC0	0.299***	0.300***	0.296***	0.297***	0.299***	0.287***	0.315***	0.310***
	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.011)	(0.013)
$\mathbb{1}$[Treatment] × NC0	−0.037**	−0.012***	−0.009***	−0.013***	−0.016***	−0.021***	−0.029***	−0.028***
	(0.014)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)
Average Daily CDDs	1.604***	1.598***	1.586***	1.573***	1.559***	1.526***	1.518***	1.535***
	(0.149)	(0.148)	(0.147)	(0.145)	(0.144)	(0.144)	(0.151)	(0.163)
Average Daily HDDs	0.500***	0.504***	0.500***	0.493***	0.484***	0.418**	0.927***	1.019***
	(0.153)	(0.151)	(0.148)	(0.144)	(0.141)	(0.165)	(0.203)	(0.306)
Bandwidth	5%	10%	15%	20%	25%	30%	35%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,008,265	2,024,211	3,056,688	4,098,107	5,173,016	5,699,991	3,865,674	3,926,154
Adjusted R^2	0.368	0.378	0.395	0.416	0.442	0.605	0.610	0.648

Note: This figure reports the results of regressions at the higher base usage quantity (i.e., the higher cutoff point) for a range of different bandwidths. Except for the bandwidth of 30%, the estimated treatment effects are not statistically significant even at the 10% level. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month. See the text for the details; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

near the higher base usage quantity could be attributed to the relatively small magnitude of the increases in the marginal price at the threshold. Specifically, the average marginal price increase at the lower base usage quantity was about 74%, whereas it was only about 18% at the higher threshold.

1.3.2 Multi-Period Household Responses to the Lagged Marginal Prices

Section 1.3.1 presents the empirical evidence that SMUD residential customers under IBP reduced their average daily electricity consumption in a billing cycle (i.e., in Period 1) as a response to the increase in the marginal price in the immediate previous billing period (i.e., in Period 0).

In this section, I examine how their electricity consumption responded to the lagged price signals in a prolonged time interval—the relationship between Period -1 and Period 1 as well as Period -2 and Period 1. In other words, I study the impact of the lagged marginal price on household electricity consumption in two- and three-month intervals. Clearly, the conditions on which my RD design relies, which are described in Section 1.2.3.2, still hold in the multi-period setting here. Nevertheless, the seasonal variation in the lower base usage quantity might significantly alter households' consumption behavior over a longer time frame. To rule out this potential confounding factor, I focus on the summer and winter seasons, during which the cutoff point for each season remained at the same level.

Figure 1.7 shows the estimated multi-period treatment effects for a set of bandwidths. The two panels on the left side of this figure are for the summer season, whereas those on the right are for the winter season. The upper and lower panels present the estimated multi-period treatment effects for households with either one of the two electric-heating rate plans and those with the RSGH rate plan, respectively.

The households choosing electric heating rate plans, whose base usage quantities moved together seasonally, demonstrated vastly different responses in the two seasons. In the summer season, they reacted to the discontinuous increases in the lagged marginal price by reducing their electricity consumption. Interestingly, the lagged price signals persisted over multiple billing cycles. Furthermore, their consumption reductions were more considerable for earlier price signals. In addition to the summer season's higher prices and much lower base usage quantity, the salience of Period -2's winter-to-summer transition in marginal prices and base usage quantities, compared to Period -1 and Period 0, could affect their responsiveness to the lagged marginal price. As described in the upper right panel, the SMUD residential customers did not respond to the lagged price signals in the winter season. Similar to the no response in the higher base usage quantity, the significantly higher cutoff point at which the first discontinuous price jump occurred in the winter season may explain this response.

In both seasons, the households selecting the RSGH rate plan showed similar responses. One notable point from their responses is that the marginal price's discontinuous increase in Period -2 had minimal impact on their electricity consumption in Period 1. In other words, the impact of the discontinuous increases on household electricity consumption tends to dissipate gradually

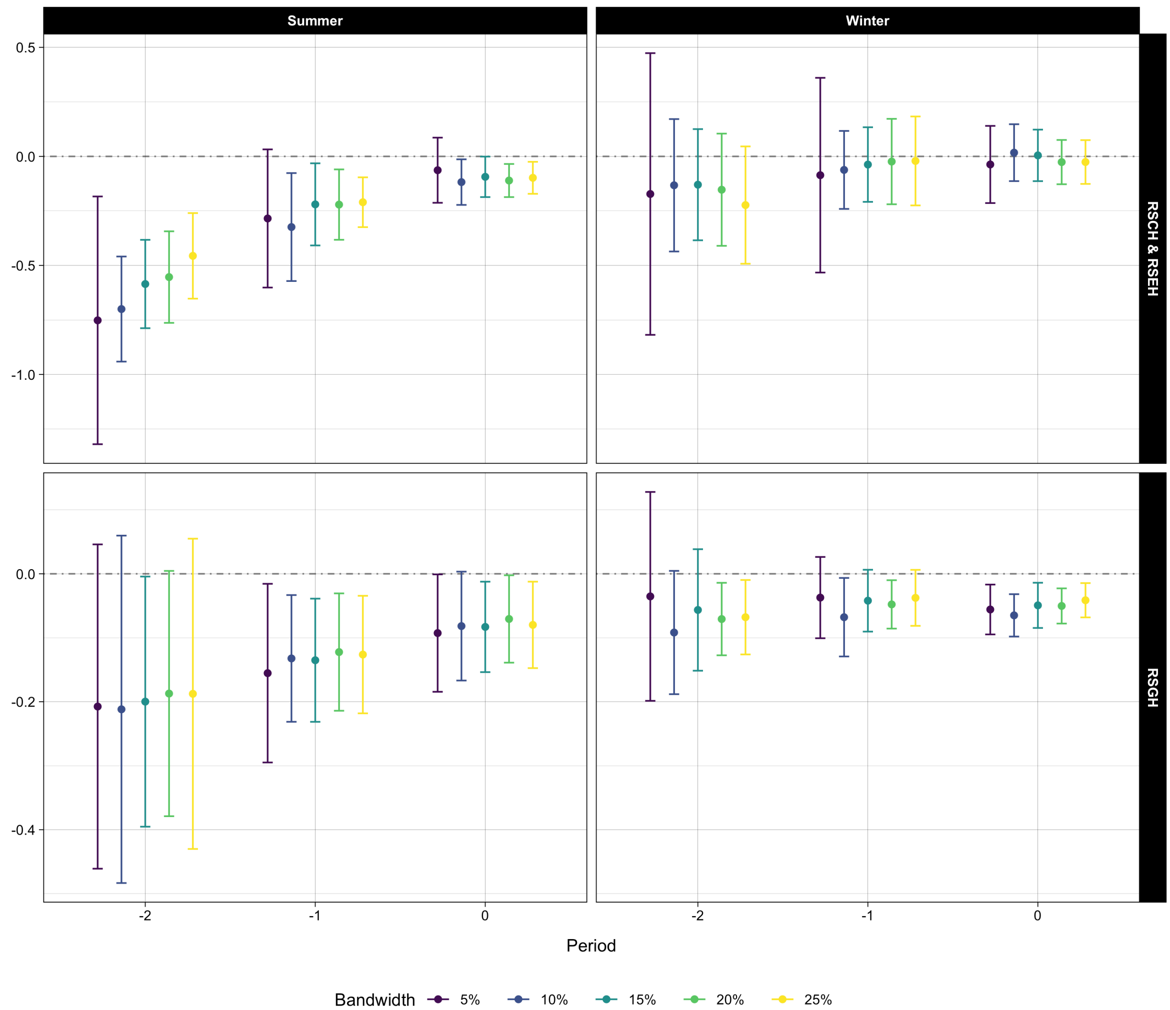

Figure 1.7: Multi-Period Treatment Effects

Note: This figure summarizes the estimated multi-period treatment effects. The over-period evolving pattern of the estimates for electric-heating households (i.e., households selecting either the RSCH or RSEH rate plan) is significantly different from that of the estimates for non-electric-heating households (i.e., households choosing the RSGH rate code). See the text for details.

over time.[15]

1.4 Policy Implications

Utilizing the Regression Discontinuity (RD) design described in Section 1.2.3.2, I show that under Increasing-Block Pricing (IBP), residential electricity consumption responded to the lagged marginal prices, informed by their monthly bill statements. Before 2010, SMUD residential

[15]The salience of the winter-to-summer transition, accompanying relatively small price increases and growths in base usage quantities, seems not to play an important role in altering households' consumption behavior.

customers had no feasible way to know, in real time, how much electricity they had consumed since the beginning of a billing cycle, how much they paid for the marginal unit, and so on. In such a situation, it seems reasonable for them to use the available information—for example, the information contained in their monthly bills, which are delivered after several days after the last day of each billing cycle—as much as possible to make decisions about their electricity use.

Nevertheless, it is undeniable that their electricity consumption responding to the lagged marginal price is suboptimal. As discussed, the marginal price to which households responded is not for the marginal unit in the current billing period but for the last unit in the previous one. In response to *wrong* price signals, SMUD residential customers reduced their electricity consumption. Moreover, they applied the lagged price signals to all units of electricity consumption in a billing month, not just the last unit in a billing month. In other words, the *informed* consumption decisions made by households, based on the lagged marginal prices, caused them welfare losses.

The issue of household welfare losses due to their response to the discontinuous change in the lagged marginal prices suggests the importance of providing seemly price information in an appropriate manner. Many studies about various time-varying electricity pricing show that households changed their consumption behavior in response to the information about consumption and prices (Faruqui and Sergici, 2011; Jessoe and Rapson, 2014; Pon, 2017; Bollinger and Hartmann, 2020). My empirical finding demonstrates that even under IBP, such information, though lagged, still plays a role in household electricity consumption. In this respect, providing household-specific as well as current price information to residential consumers, via text messages or app notifications, could encourage them to respond to *true* price signals rather than lagged ones, which in turn avoids the negative impact on household welfare. Based on the dissipating effect of intermittently salient information discussed in Gilbert and Graff Zivin (2014), a high frequency of advising the latest tailored price information might maximize the behavioral change of households in electricity consumption.

My empirical results also suggest the significance of ensuring people understand the information provided correctly. Using an up-to-date machine learning technique, Prest (2020) shows that the most critical driver of households' response to Time-Of-Use electricity pricing is their awareness of intraday price changes under the dynamic pricing. Given the empirical evidence suggested in Shaffer (2020), a subset of households in my sample may be driving the identified response to the lagged marginal prices.[16] If this is the case, the household group perceived the variation in the lagged marginal prices informed by their monthly billing statements. However, their identified response to the lagged price signals clearly indicates that they misunderstood it as price information for right now. Herefore, in my empirical context, the result of my empirical analysis could suggest that it is crucial not only to get residential consumers to be aware of price changes, but also to get them to interpret the price signals correctly.

1.5 Conclusion

In this paper, I examine how the electricity consumption of SMUD residential customers responded to the marginal price informed through monthly bill statements under Increasing-Block Pricing (IBP). In a setting with a valid regression discontinuity design, my empirical analysis shows that households, on average, reduced their electricity consumption in response to the discontinuous price change in the marginal price in the immediately preceding billing cycle. In other words, the empirical results of my analysis reveal an inefficiency of IBP. But at the same time, the interesting response demonstrates the potential to induce desired behavioral changes in household electricity consumption by providing appropriate, even lagged, price information. On top of that, the identified response, which may be driven by a subset of households in my sample, suggests that it is also important for households to correctly understand price-related information provided in order to make optimal decisions about electricity consumption.

[16] For the households showing no response to the lagged price signals, there are two possible explanations: 1) they interpreted the signals correctly; or 2) they did not pay attention to it.

Chapter 2

Prices Still Matter: How Households Adjust Their Consumption Behavior under Time-Of-Use Electricity Pricing

2.1 Introduction

Many energy utilities are shifting customers onto Time-Of-Use (TOU) electricity rate structures, which have become feasible owing to the diffusion of smart metering technology.[1] Under a TOU tariff structure, the retail price of electricity varies across periods of the day—typically with a higher "peak" price during the late afternoon hours and lower "off-peak" prices during other hours. These TOU rates are intended to reduce electricity consumption during the peak demand hours of the day when the cost of supplying the electricity and the capacity constraints on transmission networks are at their greatest. In addition to reducing peak demand for electricity, TOU pricing can also provide cost savings by shifting some of the consumption to lower demand hours or hours with excess renewable output.

Ultimately, the cost savings that can be achieved by TOU tariff structures depend on two factors. First, the extent to which TOU rates can reduce electricity consumption during peaks, and shift consumption across time, relies on how elastic consumers are to the magnitude of the price increase in the peak demand hours and the price decreases in the off-peak hours. In settings where households are unresponsive to within-day price variations, TOU prices may provide only small gains. Second, the magnitude of the benefits achieved by TOU tariffs also depends on how the resulting reductions in electricity consumption differ across days. Intuitively, reducing

[1] According to Faruqui, Hledik and Sergici (2019), residential TOU rates were offered by about 15% of all America's utilities in 2019.

electricity consumption will provide larger cost savings on days with very high electricity demand (e.g., days with extreme temperatures when demand for temperature control peaks). Suppose TOU tariffs merely cause a uniform reduction across days (e.g., households turn off their lights more often). In that case, the benefits from the time-varying rates will not vary across days. In contrast, if TOU rates induce households mainly to reduce their electricity consumption for heating or cooling, then the reductions in household electricity consumption are likely to be concentrated on peak demand days when the reductions will be the most valuable.

In light of those factors, it is necessary not only to examine how responsive a household's aggregate consumption is to the magnitude of the peak vs. off-peak price changes, but also to decompose how much of the savings in household electricity consumption stem from reductions in the use of energy services that systematically vary across days (e.g., temperature control), in order to fully understand the full impacts of TOU electricity pricing on household electricity consumption.

While many evaluations of various dynamic electricity prices, including TOU programs, consistently document reductions in electricity consumption during peak hours (Faruqui and George, 2005; Faruqui and Sergici, 2011; Faruqui, Sergici and Akaba, 2013), the literature often finds that households' consumption is quite inelastic to the magnitude of the within-day price changes (Allcott, 2011; Jessoe and Rapson, 2014). Notably, Prest (2020) finds that, in a TOU pricing experiment in Ireland, households were highly insensitive to the incremental increases in the peak rate.[2] That is, residential consumers seemed to respond only to the existence of the within-day price changes and not the magnitude of the within-day price changes. This paper aims to re-examine the TOU program evaluated by Prest (2020) to understand why household's aggregate consumption is so inelastic with respect to the magnitude of the within-day price changes.

When re-measuring how sensitive residential consumers are to TOU tariffs, I decompose their electricity consumption into two distinct channels of consumption instead of merely investigating their consumption as a whole: 1) electricity consumption for non-temperature-control uses (e.g., lighting, operating appliances, and cooking), and 2) electricity consumption for temperature-control uses (e.g., cooling and heating). My empirical analysis focuses on those two broad cate-

[2]This paper, which also utilizes the CER experiment datasets, expresses the results as follows: "Most of the overall response comes at the smallest price increase, with higher prices yielding strongly diminishing returns."

gories of electricity consumption for two reasons. First, the two types of electricity consumption react differently to outdoor temperatures. Electricity consumed for temperature control will undoubtedly depend on outdoor temperatures. For example, more electricity will be used to heat on cold days compared to mild days. By contrast, electricity used for other non-temperature-control services will be largely independent of outdoor temperatures. These enable me to estimate how much electricity is consumed for each category by using temperature variation. Second, the two distinct electricity consumption categories may respond differently to TOU prices. For instance, TOU electricity pricing may cause households to relocate some non-temperature-control-driven services to non-peak hours without changing aggregate consumption across a day (Herter and Wayland, 2010; Harding and Lamarche, 2016). In contrast, if TOU rates induce them to lower their electricity use for heating, then there could be reductions in consumption across all hours.

My study examines 30-minute interval household metering data collected from a TOU pricing experiment conducted from July 2009 to December 2010 by the Commission for Energy Regulation (CER), the electricity and natural gas sector regulator in Ireland.[3] While the vast majority of homes in the sample utilized oil and gas as their primary energy source for space and water heating, a sizable amount of electricity was still used for heating in those homes. Notably, residential electricity consumption peaked during the winter months, typically reaching levels approximately 1.5 times higher than the consumption observed during the mild summer months. Using the observed household consumption throughout the day and measurements of the daily temperatures in Ireland, I estimate 1) the changes in temperature-control-driven and non-temperature-control-driven consumption, respectively, caused by the TOU program, 2) how these consumption changes vary with the average daily outdoor temperature—more precisely, daily Heating Degree Days (HDDs)—, and 3) how these consumption changes vary with the magnitude of the peak-rate-period price change.

From my empirical analysis, I document two key findings. First, the two broad categories of household electricity consumption were responsive to incremental changes in the peak-rate-period price, but in different ways. In the peak rate period, households' non-temperature-control-driven electricity consumption was highly sensitive to the magnitude of the price changes. On the other hand, there is no evidence that the reduction in temperature-control-driven electricity consumption during the peak rate period increased as the size of the incremental price changes

[3] The CER changed its name to the Commission for Regulation of Utilities (CRU).

grew. Instead, there is weak evidence demonstrating that in the peak rate period, the reduction in temperature-control-driven electricity consumption went towards zero as the price increased. Interestingly, due to the opposite relationship between demand reductions and price changes in the two channels of electricity consumption, the high sensitivity of household electricity consumption in response to TOU pricing in the peak rate period was masked. In other words, when the estimated reductions in electricity consumption originating from the two channels are aggregated, the difference in the combined reduction between tariff groups is seemingly dampened because of the opposite correlations.[4] Indeed, this finding precisely explains the price insensitivity discussed in Prest (2020).[5]

Even in the hours leading up to and following the peak rate period (denoted the pre- and post-peak hours/periods, respectively), the TOU tariffs also induced changes in households' demand for electricity, which cannot be explained simply by price drops in the hours surrounding the peak rate period. In the experiment, the households under the TOU tariff structures experienced price increases during the peak hours, whereas they faced decreases in the price they paid for electricity consumption in the hours surrounding the peak rate period. Moreover, the higher the price the households had to pay in the peak rate period, the lower the off-peak prices (i.e., the day and night rates) they had to pay. My regression analysis shows that households reduced their non-temperature-control-related electricity consumption in both off-peak periods. In other words, the load-shedding in the peak rate period spilled over into the pre- and post-peak hours, during which prices fell. On top of that, load-shifting from the peak to the off-peak hours, incentivized by across-rate-period price differences, seemed to occur, too. Furthermore, the revealed relationship between the size of the load-shifting and the magnitude of the peak-hour price change confirms the economic intuition about the price incentive for the load relocation. My analysis also suggests that the load-shifting only partly, or just barely, offset the spillovers. In the aggregate, in both off-peak periods, the more considerable the price increase in the peak rate period, the smaller the reduction.

For temperature-control-driven consumption changes, my empirical analysis indicates that a different pattern emerged in pre- and post-peak hours. I find that during the pre-peak hours, households' temperature-control-driven electricity usage fell, and those reductions got larger as the magnitude of the price jump in the peak rate period increased. That is, households exposed

[4] There were four tariff groups in the CER experiment. See Figure 2.1.

[5] See *5.3 Price Insensitivity* in Prest (2020).

to a higher peak-demand-hour price appeared to reduce their pre-peak usage for heating by larger amounts. In contrast, my analysis demonstrates that households' temperature-control-driven electricity usage rose during post-peak hours. As opposed to the consumption changes in the pre-peak hours, these growths in electricity usage for heating during the post-peak hours got smaller as the size of the peak-hour price change increased. Altogether, in both non-peak periods, due to the opposite directional changes in the two categories of household electricity consumption, households' sensitive responsiveness to the TOU tariff structures was muted, as it was in the peak rate period. Interestingly, those temperature-control-relevant consumption changes near the peak rate period were observable only when outdoor temperatures were low enough.

The second key finding from my empirical analysis is that the reduction in households' temperature-control-related electricity consumption during the peak hours showed a U-shaped profile over daily HDDs. The nonlinearity in TOU-tariff-induced temperature-control-associated reduction in household electricity consumption over households' daily heating needs discloses a veiled feature of TOU electricity pricing: its day-varying effects on the temperature-control-related part of residential electricity consumption. Suppose that the reductions obtained by adopting TOU prices stem entirely from the non-temperature-control use of electricity. In that case, the degree of reductions does not vary across days because it is nearly irrelevant to across-day temperature variation. My empirical results, however, indicate that on days with moderate heating needs, a sizable reduction in household electricity consumption stemmed from electricity usage for temperature control during the peak hours. For instance, in the case of the household subgroup that experienced a six-dollar price increase in the peak rate period, more than two-thirds of the reduction in their electricity consumption came from temperature-control-related consumption when the value of daily HDDs was ten. Consequently, even though the TOU electricity pricing only has intraday price variation, the pricing already induces a substantial reduction in electricity consumption for heating on typical winter days, in terms of daily HDDs, in Ireland. Therefore, on those days, the additional gains captured by switching TOU prices to Real-Time Pricing (RTP) will likely be smaller than many economists have thought.[6]

To sum up, the results from my empirical analysis extend the previous work by isolating

[6]Under RTP, retail prices vary across not only hours of days but days according to contemporaneous generating costs.

temperature-control-associated reduction in household electricity consumption from the entire TOU-tariff-induced demand declines. My results demonstrate that in and near the peak hours, the changes from each of the two channels of electricity consumption are responsive to the magnitude of the price changes in the peak rate period. That is, in determining the electricity consumption level within a home under TOU tariff structures, not the mere existence of price changes, prices themselves—more clearly, the magnitude of the price increase in the peak hours—still matter. Moreover, the day-varying performance of TOU electricity pricing suggests a vital policy implication of an alternative electricity pricing that internalizes an additional layer of dynamics by nonlinearly synchronizing price increases in the peak hours with daily HDDs, causing a more significant reduction in household electricity consumption on extremely cold days.

2.2 Data

2.2.1 Description of CER Experiment

The Commission for Energy Regulation (CER), the regulator for Ireland's electricity and natural gas sectors, conducted the Smart Metering Electricity Consumer Behavior Trial (hereafter, the "trial") between July 2009 and December 2010.[7] As part of the Smart Metering Project initiated in 2007, the trial's purpose was to assess the impact of various TOU tariff structures, along with different Demand-Side Management (DSM) stimuli, on residential electricity consumption. The CER carefully recruited households to construct a representative sample of the national population. Opt-in to the trial was voluntary. Participants received balancing credits not to incur any extra costs than if they were on the regular electric tariff (i.e., the flat rate of 14.1 cents per kWh). Also, they received a thank-you payment of 25 cents after pre- and post-trial surveys. All credits were distributed outside the treatment period to avoid unintended effects on participants' electricity consumption.[8]

The households who voluntarily opt-in to the experiment were randomly assigned to control and treatment groups.[9] Baseline electricity consumption data were collected during the second

[7] The detail about the CER experiment presented hereinbelow is a summary of Commission for Energy Regulation (2011).

[8] While the first balancing credit was paid at the end of the base period (i.e., in December 2009), the participants received the second one at the immediate month after the treatment period (i.e., in January 2011). And the after-survey payments were credited to their bill with the balancing credits.

[9] The optimal sample size for the trial was determined to be 4,300 participants in the design phase. In the

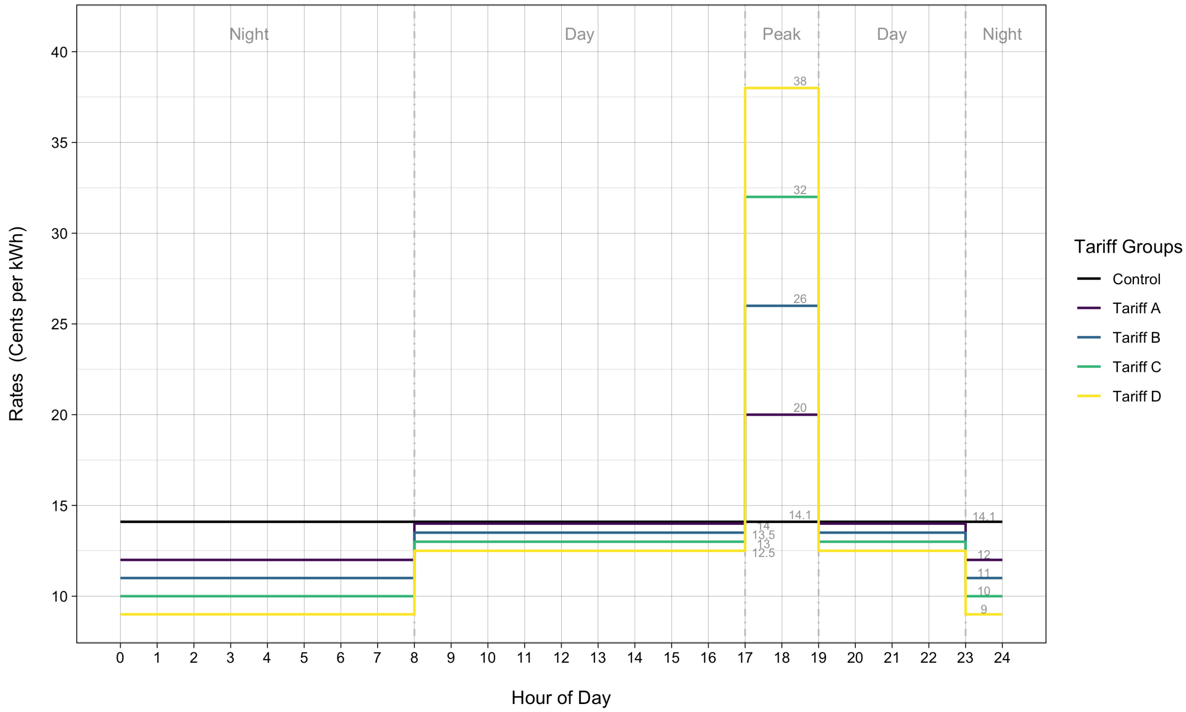

Figure 2.1: Time-Of-Use Pricing Structures

Note: This figure illustrates the CER experiment in terms of TOU tariff structures. The households in the control group were subjected to a flat rate (i.e., 14.1 cents per kWh) during the entire experiment period. On the contrary, the treated households are assigned to one of four TOU tariff groups. And for each tariff group, there were three rate periods: night, day, and peak. Only the unit rate in the peak rate period was higher than the flat rate.

half of 2009 (i.e., July to December 2009), while the treatment period was from January through December 2010. All treated households received two kinds of treatments simultaneously: 1) one of four TOU tariff structures and 2) one of four DSM stimuli, described in detail later. In other words, there were 16 distinct treatment subgroups. The CER provided the treated with a fridge magnet and stickers to facilitate accustoming them to the TOU pricing schemes.[10] On the contrary, the households allocated to the control group remained on the normal flat tariff.

The four TOU tariff structures had different prices during each of the three rate periods in a

allocation phase, 5,028 households were assigned to the control and treatment groups to consider participant attrition. The published CER experiment data include electricity consumption data only for 4,225 households.

Both papers point out that voluntary opt-in might cause bias in the estimated treatment effect. Refer to *5.5.3 External Validity* in Prest (2020) and *5.1 Addressing Self-Selection* in Pon (2017).

[10]The fridge magnet and stickers outlined the timebands during which different prices were applied. Moreover, they were tailored for each tariff group.

day. The day in the treatment period was divided into three periods: 1) peak rate period from 5:00 p.m to 7:00 p.m., 2) day rate period from 8:00 a.m. to 5:00 p.m. and from 7:00 p.m. to 11:00 p.m., and 3) night rate period from 11:00 p.m. to 8:00 a.m. As illustrated in Figure 2.1, the order of magnitude in rate changes during the peak rate period is the opposite of that for the rest of the rate periods. The reason for designing the tariff structures in such a way is to enable participating households to face similar energy bills on average when maintaining their electricity consumption pattern, regardless of the rate structures to which they were assigned.

The four DSM stimuli differed in the degree or the frequency of feedback on each household's electricity usage information. The control group received their bills in the same cycle (i.e., bi-monthly). On the contrary, all households assigned to the treatment group received a detailed energy usage statement combined with their bill, including their detailed weekly usage, average weekly costs, tips on reducing electricity use, and comparisons to peer households. The first stimulus subgroup received a bill with a detailed energy statement bi-monthly, while the second subgroup received the documents every month. An electricity monitor, which displays their usage against their pre-set daily budget, was also provided for the households allocated to the third DSM stimulus subgroup. The last stimulus subgroup received an Overall Load Reduction (OLR) incentive. Under the OLR incentive, the households that reached their 10% reduction target over the eight-month period beginning May 2010 were rewarded with 20 Euros.[11]

2.2.2 Description of CER Experiment Data

The CER experiment dataset disseminated by the Irish Social Science Data Archive (ISSDA) consists of participating households' electricity consumption and survey data.[12]

Throughout the baseline and treatment periods, meter reads for residential participants were recorded in 30-minute intervals. The high granularity of the electricity consumption data generated from a well-designed experiment enables quantifying the energy savings when transferring to TOU electricity pricing for each of the three rate periods.

The survey data contains participants' responses to more than 300 questions in pre- and post-trial surveys. The primary purpose of the two surveys was to gather trial-associated experiential

[11] A household's reduction target in electricity consumption was set based on the participant's actual usage during the first four months of the treatment period. And the households in the last DSM stimulus subgroup were updated on their progress with each bi-monthly bill.

[12] Many papers have explored the CER dataset with different focuses. See Carroll, Lyons and Denny (2014), McCoy and Lyons (2016), Cosmo and O'Hora (2017), and Di Cosmo, Lyons and Nolan (2014).

Table 2.1: Treatment and Control Group Assignments

Stimuli	Tariffs					Total
	Control	A	B	C	D	
Monthly Bill	0	79	37	89	28	233
Bi-Monthly Bill	0	81	34	76	34	225
Bi-Monthly Bill + IHD	0	79	22	86	30	217
Bi-Monthly Bill + OLR	0	90	27	84	34	235
Control	260	0	0	0	0	260
Total	260	329	120	335	126	1,170

and attitudinal feedback from the households. The surveys also included questions intended to collect residential participants' socio-demographic characteristics. In addition, questions about the physical attributes of their house were included in the surveys.

My empirical analysis throughout this paper uses a longitudinal sample that consists of observations satisfying certain conditions only. First of all, the sample is constructed by including observations only for the second half of each experiment period.[13] From this sample, I keep observations for non-holiday weekdays in the published electricity consumption data because the TOU rates were active just on those days. And then, only households that continuously exploited non-electric fuels for their space and water heating during the experiment periods (i.e., the baseline and the treatment periods) are preserved in the sample.[14] Moreover, among the non-electric-heating households, those with unreliable meter reads are excluded from the sample.[15]

[13] I exclude the observations for the first half of the treatment period because there is no counterpart observation in the baseline period.

[14] From the survey data, it is possible to find out what type of fuel each responding household used for each heating purpose during each period.

There are two reasons why only non-electric-heating households are exploited in the following empirical analysis. First, in Ireland, non-electric fuels, such as oil, gas, and solid fuels, fulfill most of the residential heating demand. Specifically, according to Sustainable Energy Authority of Ireland (2022), only 4% of Irish households utilize electricity to heat their space and water. Therefore, with respect to fuels for heating in Ireland, the sample consisting of non-electric heating households only is representative. Second, as Figure 2.4 demonstrates, even non-electric-heating households consumed more electricity as temperatures decreased. In other words, electricity is still essential for non-electric-heating households to warm their space or water. Hence, the sample, including non-electric-heating households only, is well aligned with one of the primary purposes of this research: to evaluate the impact of TOU pricing on temperature-control-driven residential electricity consumption separately.

[15] To be specific, the residential participants who had no consumption for eight days or more are excluded from

This process results in 1,170 households. Table 2.1 summarizes the assignment distribution of the 1,170 households.

The control and treatment groups in the sample are largely balanced, as shown in Table 2.2. Although several variables are statistically significant at the 5% level, the Bonferroni familywise p-value is not significant at that level. The absence of differences between the two groups over many observables are consistent with previous studies examining the CER experiment dataset.[16]

2.2.3 Description of Weather Data

In this research, weather data are an essential element. The main interest of most TOU papers has been to measure how consumers respond to TOU prices or the heterogeneity in their responsiveness across different information stimuli. And the studies have focused on aggregate electricity consumption, consisting of consumption for a wide range of end-use types. Hence, those studies usually do not control temperature variations directly. For example, Pon (2017) and Prest (2020), which also exploited the CER experiment dataset, added weak-of-sample and month-by-year fixed effects (FEs) to their specifications, respectively, in order to control for variations in electricity usage due to seasonal changes. On the other hand, a novel approach adopted in this paper is to decompose household electricity consumption into two broad categories: non-temperature-control- and temperature-control-associated electricity consumption.[17] Since the electricity consumption for temperature-control use is significantly driven by weather, particularly temperatures, it is necessary to link the 30-minute interval consumption data with reliable weather data that is of an appropriate level of resolution.

I utilize average daily temperatures in my empirical analysis. More granular temperatures, like hourly temperatures, are not a dominant determinant of temperature-control-driven electricity consumption at a point in time. It is not easy to believe that households adjust their

the sample. In addition, I drop the meter reads for the days when several participating households' consumption data were missed.

Although I utilize the sample satisfying the following criteria too for the empirical analysis, applying the criteria does not change the results: 1) Exclude the day immediately following the end of daylight-saving time due to noticeably different consumption levels in the same hours of the day; 2) Drop the observations for the last five days of the baseline and treatment periods because of extraordinarily high electricity demand on those days.

[16] To check the balance between the control and treatment groups, Prest (2020) employs a linear probability model, while a probit model is used in Pon (2017).

[17] Details of the approach are discussed in Section 2.3.2.1.

Table 2.2: Summary Statistics and Differences in Means

	Control		Treatment		Difference		
	Mean	(S.E.)	Mean	(S.E.)	Mean	(S.E.)	*p*-value
Electricity Consumption during Baseline Period (kWh)							
Daily	22.122	(0.674)	23.529	(0.379)	1.407	(0.773)	0.069
Hourly	0.939	(0.028)	0.996	(0.016)	0.057	(0.032)	0.074
Hourly, Night Rate	0.524	(0.018)	0.560	(0.010)	0.035	(0.021)	0.088
Hourly, Day Rate	1.128	(0.034)	1.193	(0.019)	0.065	(0.039)	0.095
Hourly, Peak Rate	1.537	(0.053)	1.642	(0.029)	0.105	(0.060)	0.080
Demographics							
Age Group: 65+?	0.277	(0.028)	0.225	(0.014)	-0.052	(0.031)	0.096
Education: Primary or less?	0.208	(0.025)	0.144	(0.012)	-0.064	(0.028)	0.022
Education: Secondary?	0.462	(0.031)	0.457	(0.017)	-0.005	(0.035)	0.889
Unemployed?	0.081	(0.017)	0.101	(0.010)	0.020	(0.020)	0.304
Number of People over 15 in Home	2.488	(0.061)	2.506	(0.032)	0.019	(0.077)	0.808
Number of People under 15 in Home	1.754	(0.060)	1.964	(0.035)	0.210	(0.138)	0.132
Housing Characteristics							
Owned House?	0.904	(0.018)	0.932	(0.008)	0.028	(0.020)	0.165
Number of Bedrooms	3.335	(0.054)	3.465	(0.028)	0.130	(0.061)	0.035
Timer for Space Heating	0.792	(0.025)	0.802	(0.013)	0.010	(0.028)	0.728

Note: In the table, variable descriptions with question mark suggest that these variables are binary.

electricity consumption according to ever-changing outside temperatures elaborately and instantly.[18] Furthermore, as shown in Figure 2.2, their electricity demand is the lowest in the early morning, the coldest time of the day. Considering those two points, I measure the TOU-tariff-induced reductions in electricity consumption conditional on the average heating needs on a given calendar day.

I exploit hourly temperature data for the Dublin airport weather station, provided by Met Éireann, Ireland's National Meteorological Service, to compute average daily temperatures. There is no available location information in the published CER experiment dataset for privacy and security reasons. Therefore, it is impossible to match a participant's consumption data with the weather data of the closest weather monitoring station to him. But fortunately,

[18]Refer to *3.4 Household Response to Dynamic Prices Exhibits Nontrivial Costs of Action That Impede Peak Reductions* in Harding and Sexton (2017).

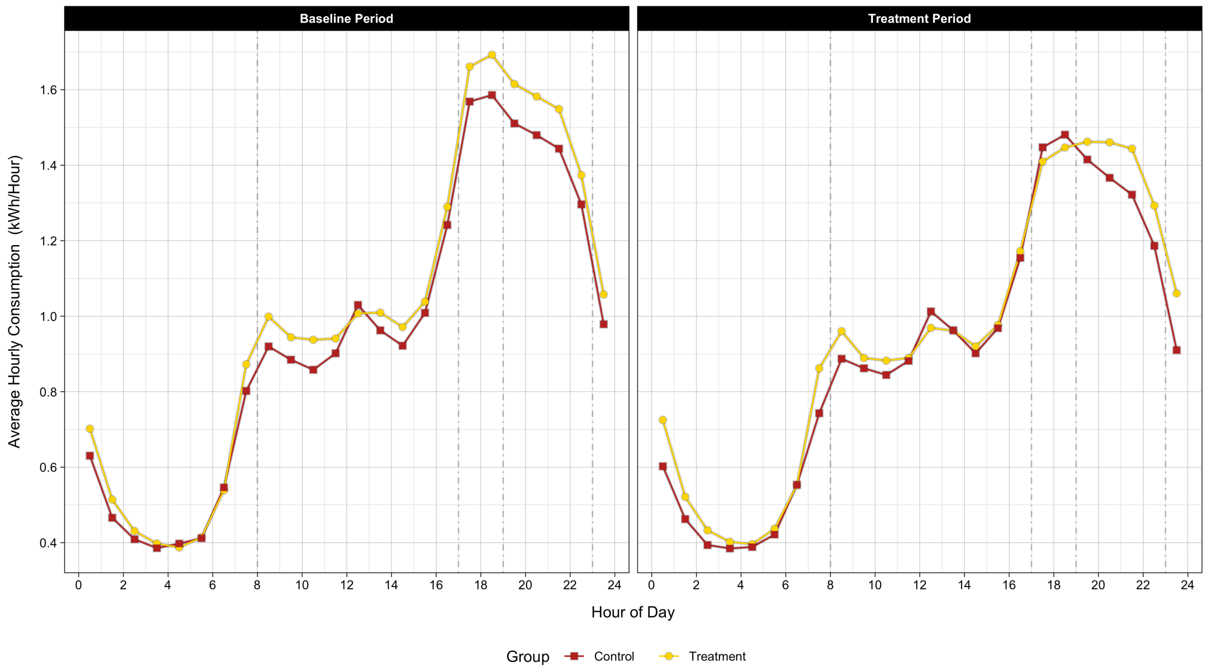

Figure 2.2: Average Hourly Electricity Consumption by Time of Day

Note: The figure shows, during each experiment period, household average hourly electricity consumption for the control and treatment groups, respectively. In general, during the baseline period, households assigned to the treatment group consumed more electricity at a given hour of the day. Although both groups reduced their electricity consumption during the treatment period, the reduction in electricity consumption for the treatment group was much more remarkable for the treatment group than for the control group.

in Ireland, temperatures do not vary much across areas for a given day. As demonstrated in Table A.4, the temperature correlations between the Dublin station and stations near densely populated cities are evident. Because of the close correlations, I use the mean daily temperatures obtained by averaging the Dublin airport station's hourly temperatures as the representative temperatures in the following analysis.

Using the average daily temperatures, I calculate daily Heating Degree Days (HDDs). Instead of 65 degrees of Fahrenheit ($^{\circ}F$), a normal base temperature in the United States, $60^{\circ}F$ is utilized to compute daily HDDs, according to Liu and Sweeney (2012). Figure 2.3 shows that many days in the treatment period had lower average daily temperatures than the lowest one during the baseline period. The evolving pattern of temperature-control-driven demand for electricity on days with extreme temperatures could be significantly different under distinct rate structures—e.g., flat and TOU rates. If this is true, the lack of counterfactual consumption observations

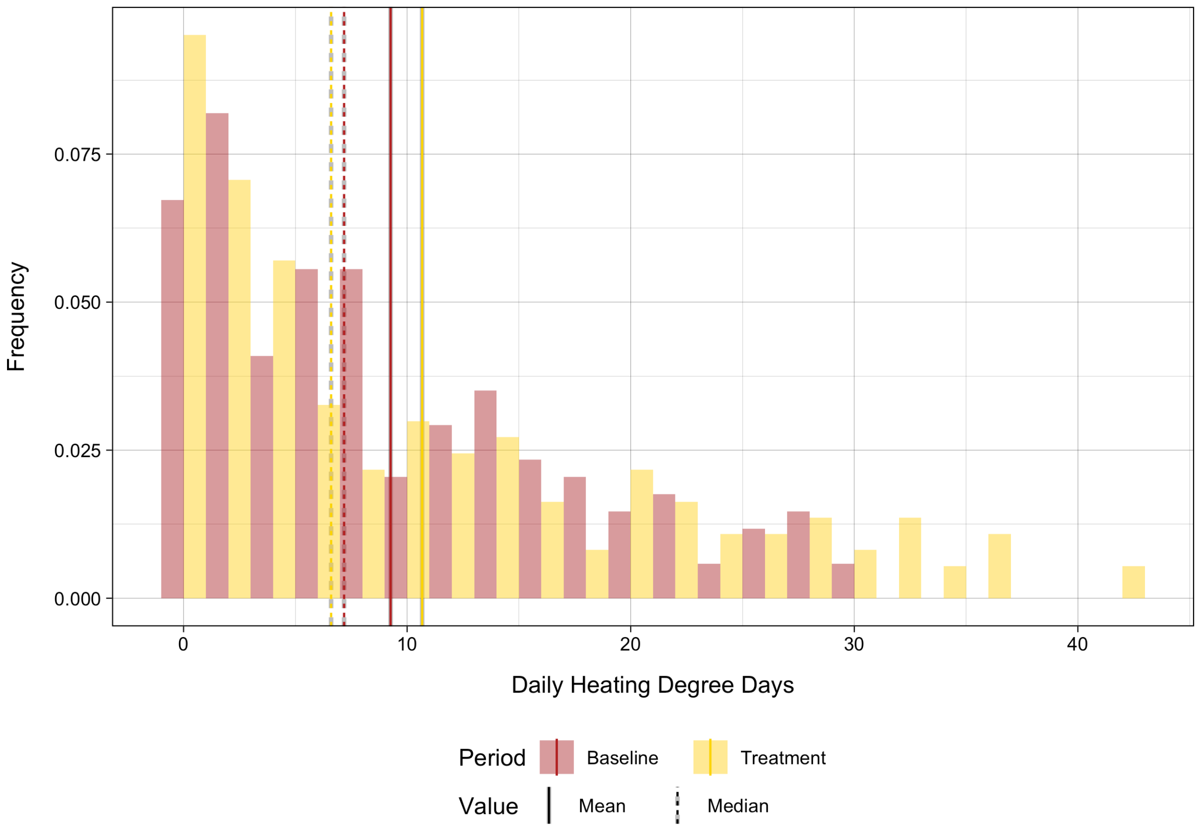

Figure 2.3: Distribution of Daily Heating Degree Days during Experiment Periods

Note: This histogram shows the distribution of daily HDDs, with the mean and median values, in each experiment period. Only the second halves of 2009 and 2010 are utilized to generate the histogram.

will cause bias in the measured impact of introducing TOU pricing on household electricity consumption. So, I drop observations for those days in the treatment period when constructing the sample to address the potential threat to the identification.

2.2.4 Empirical Strategy

Figure 2.4, showing not only household average daily electricity consumption over temperature (in Panel A) but also percentage changes in electricity consumption (in Panel B), clearly demonstrates the motivation of this research.[19] As illustrated in Panel A of the figure, household demand for electricity grew gradually as the temperature decreased. That is, for Irish households, in addition to temperature-insensitive electricity demand (i.e., for non-temperature-control uses),

[19] An important feature also stands out from the figure: the minimum household electricity consumption occurred at around $60^{\circ}F$. This phenomenon supports the setting of the reference temperature for calculating daily HDDs at the very level.

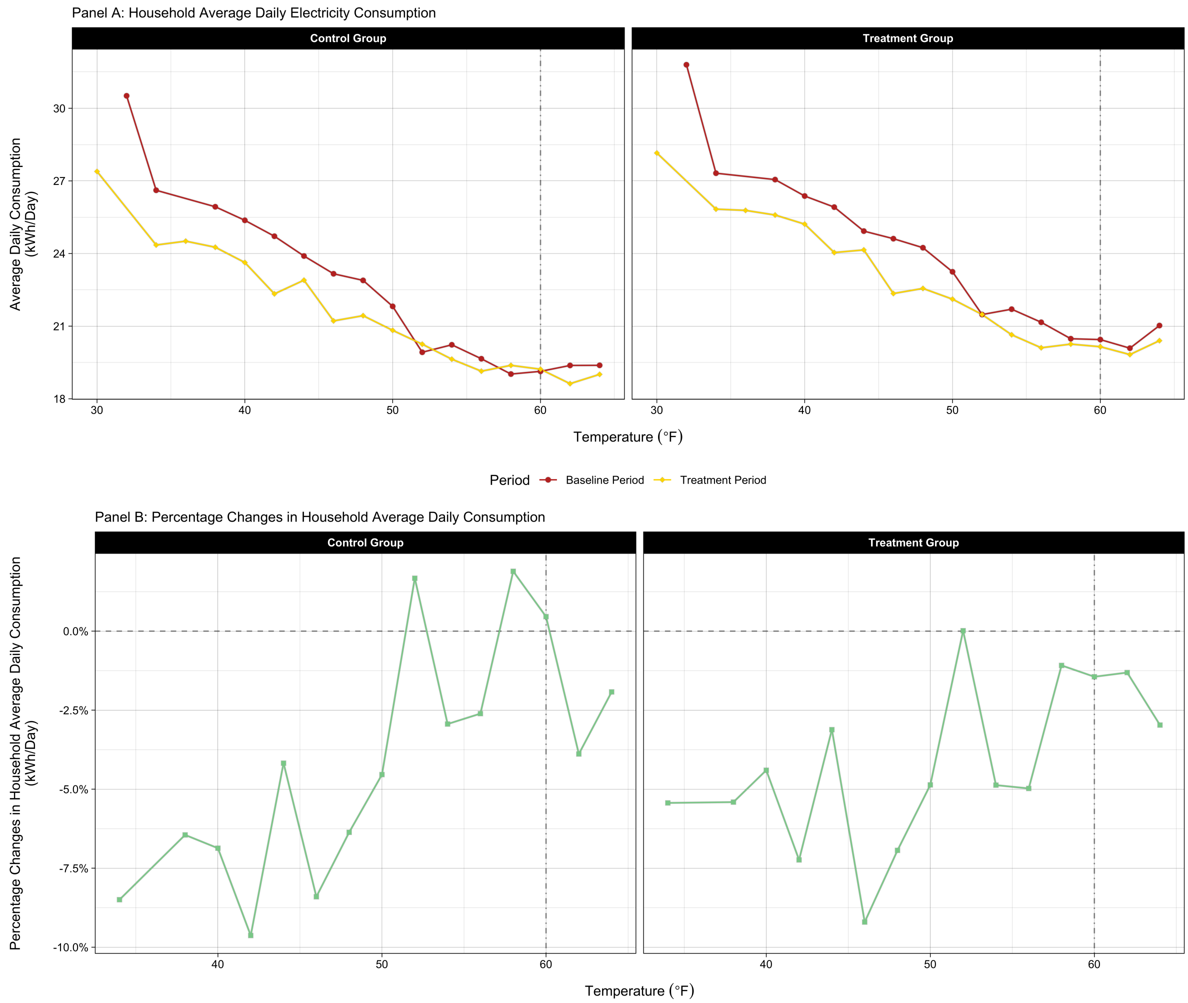

Figure 2.4: Pre- and Post-Treatment Household Average Daily Electricity Consumption

Note: Panel A in this figure illustrates, for each group, how within-household average daily electricity consumption evolved over average daily temperatures during each experiment period. In addition, Panel B of the figure demonstrates the percentage changes in residential electricity consumption after the deployment of TOU tariff structures at different mean daily temperatures. The treatment group showed larger percentage reductions on typical winter days (roughly speaking, when the average daily temperature was lower than the value of $45°F$), while the control group exhibited wider percentage reductions on exceptionally cold days in Ireland.

there was a sizeable electricity demand for heating (i.e., for temperature-control uses), which seems to be highly responsive to temperature variations. In this research, I determine not only how much variations in household electricity consumption occurred, on average, in response to the deployment of the TOU tariffs but also how their impact varied according to daily HDDs. In other words, the dynamic-pricing-causing effects on for-heating and non-for-heating electricity uses are separately estimated to figure out the primary source of electricity savings. As shown in the figure, households in the control group consumed less electricity during the treatment period, especially on days with low temperatures, although their percentage reductions seem less than those of the treated households.[20] In light of this, it is necessary to employ an identification strategy that accounts for the before and after differences in household electricity consumption under the traditional tariff structure (i.e., a flat rate of 14.1 cents per kWh for all hours).

I employ a Difference-In-Differences (DID) approach to estimate the electricity savings caused by the TOU price program. The CER experiment dataset primarily utilized in the following empirical analysis was generated from a carefully developed Randomized Controlled Trial (RCT). So, in principle, the effect of the TOU tariffs on household electricity consumption can be measured simply through the difference in average usage between the two groups during the treatment period.[21] However, as discussed, there exist non-trivial differences in electricity demand between the control and treatment groups during the baseline period. Following the previous studies exploiting the same data, I utilize a DID estimator to address the possible source of bias.

I include daily HDDs as an explanatory variable directly in my econometric models. In the previous papers using the identical dataset, Fixed-Effects (FEs) were utilized to control for time-varying factors influencing household electricity consumption. Since those studies focused on quantifying how households responded, on average, to the TOU price regimes newly introduced, adding such FEs to their models served their research purpose. In other words, they did not need to explicitly model the relationship between temperature and household electricity consumption to estimate the Average Treatment Effects (ATEs). However, a primary interest of this research is to understand how electricity savings vary with the temperature after shifting to TOU prices. Therefore, more direct controls rather than FEs, not sweeping out temperature variations across days, are required in my empirical analysis. For that reason, I extend a typical panel DID specification and allow the treatment effect to vary as a function of daily HDDs.[22] That is, I estimate the ATEs of the dynamic prices on household electricity demand

[20] In Panel A, non-treated households consumed more electricity during the baseline period, especially on days with higher heating needs. The fact that for a given temperature bin, the total daily HDDs during the baseline period were generally greater than those during the treatment period is a plausible explanation for the phenomenon.

[21] Because random assignment of participating households puts selection bias right, observed differences in electricity consumption between the control and treatment groups after introducing the TOU tariffs are only attributable to their differences in exposure to the time-varying electricity prices.

[22] Under three identifying assumptions, applying a DID strategy to measure electricity savings obtained from

by exploiting the within-household electricity consumption changes across not only rate periods but temperatures.[23]

A caveat to my empirical analysis is that a tariff group in my sample's treatment group consists of four subgroups that were subject to one of the four different DSM stimuli. Because of this, part of the estimated ATEs should be attributable to the DSM stimuli. But as shown in Table 2.1, the proportions of the four distinct DSM stimuli, constituting each tariff group, are similar in my sample. Therefore, within a tariff group, a specific DSM stimulus is unlikely to play a prominent role in causing changes in household electricity consumption.

adopting the TOU prices makes sense. First, the parallel trend assumption is required for the DID estimator. Considering that the 30-minute interval meter reads for participating households were collected during the trial, the assumption implies that the pre-treatment-period load profile for the treated households should be very similar to that for the non-treated households. Figure 2.2, showing average within-day load profiles for the two groups during the baseline period, supports the plausibility of the parallel trend assumption. In addition, the electricity consumption profile for the control group illustrated in Figure 2.6, which smoothly evolved over the entire experiment period although heavily fluctuated daily, suggests its high reliability as a counterfactual under the assumption. The assumption of common temporal shocks is the second identifying assumption necessary for the plausibility of the identification strategy employed. This assumption implies that a treatment-status-irrelevant unexpected event occurring at the same time as or following the deployment of the dynamic prices should have the same impact on both the control and treatment groups. Although the common shocks assumption cannot be tested directly, the similar trends in electricity demand profiles for the control and treatment groups shown in Figure 2.6 support the assumption required for the DID approach. Third, the stable unit treatment value assumption (SUTVA) must hold too. The SUTVA requires that introducing the TOU prices did not affect the electricity consumption of the untreated households. That is, the SUTVA allows no spillovers. During the recruitment process, the locational distribution of the participating households was aligned with that of the total Irish population to construct a representative sample of the national population. Because only a few thousand households scattered geospatially participated in the nationwide experiment, it is unlikely that the treated households influenced the households allocated to the control group. This again supports the SUTVA required under the DID identification strategy.

[23]The attrition rate during the RCT was about 20%. The main reasons for participant attrition were changes in tenancy and supplier. Due to such imperfect compliance, the estimates must be interpreted as local average treatment effects (LATEs). However, according to Commission for Energy Regulation (2011), attritions were unlikely to be associated with the RCT. Furthermore, the level of attritions varied only marginally across treatment status.

2.3 Empirical Analysis and Results

2.3.1 Household Average Responses to Time-Of-Use Electricity Pricing

2.3.1.1 Half-hourly Average Treatment Effects

Utilizing a panel DID identification strategy, I first measure the impact of the TOU prices on 30-minute-interval household electricity consumption. To obtain the Average Treatment Effect (ATE) for each half-hour interval, I estimate the following specification:

$$kWh_{itw} \;=\; \beta_w \mathbb{1}\big[\text{Treatment \& Post}\big]_{it} \;+\; \alpha_{iw} \;+\; \gamma_{tw} \;+\; \delta_m \;+\; \epsilon_{itw} \tag{2.1}$$

The term kWh_{itw} is the electricity consumption by household i on the day t during the half-hourly time window w. The indicator variable $\mathbb{1}\big[\text{Treatment \& Post}\big]_{it}$ is equal to 1 only if household i is in the treatment group and the day t is in the treatment period. The terms α_{iw}, γ_{tw}, and δ_m are household-by-half-hourly-interval, day-of-sample-by-half-hourly-time-window, and month-of-year fixed effects, respectively. In the specification, the point estimates of β_w, representing the ATE for each 30-minute interval w, are the parameters of interest. I cluster the standard errors at the household and the day of experiment levels to correct for serial correlation.

Figure 2.5 summarizes the estimated ATEs in the form of a time profile. As already demonstrated in Prest (2020), peak hours (i.e., from 5:00 p.m. to 7:00 p.m.) show dominant electricity savings. The figure also demonstrates reductions in household electricity consumption not only in most of the meter readings prior to the peak rate period but also in three successive meter readings right after the period, even though the reductions, with two exceptions, are not statistically significant. The insignificant reductions in household electricity consumption are interesting because TOU prices in off-peak hours (i.e., prices in the night and day rate periods) were lower than the flat rate in the baseline period. The counterintuitive changes might indicate that households preemptively adjusted their consumption behavior to avoid the incident of paying higher prices. In other words, the peak-hour price increases under the TOU program were likely to cause some spillover effects in the hours leading up to and following the peak rate period. To explore whether households responded to the TOU program outside of the peak rate period as well or not, in the following empirical analysis, I will also pay attention to the off-peak hours, particularly the hours surrounding the peak rate period.

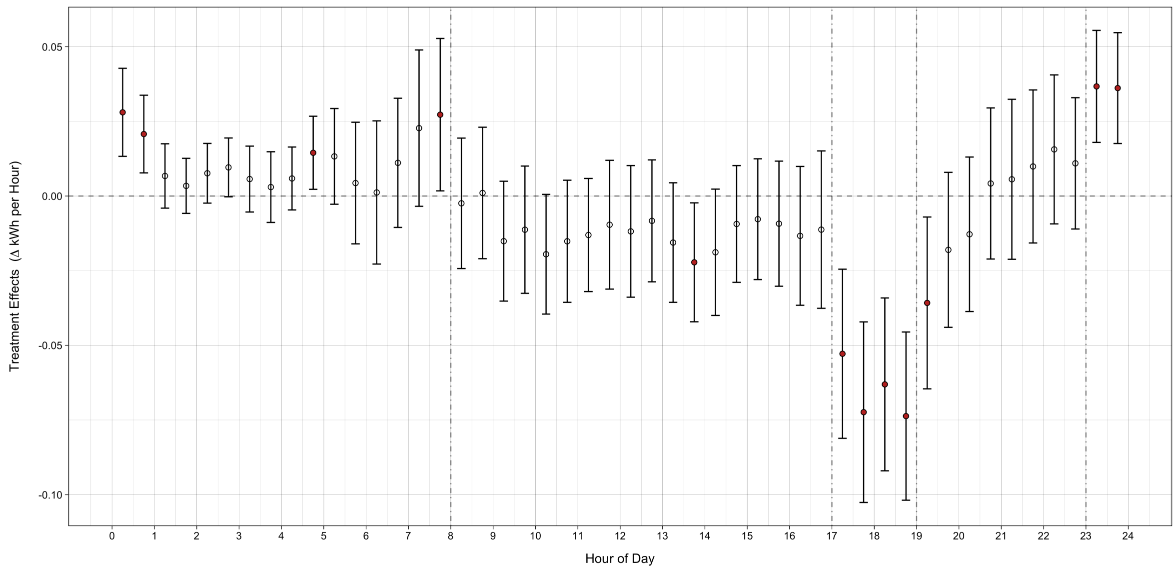

Figure 2.5: Half-hourly Average Treatment Effects

Note: This figure depicts the time profile of half-hourly average treatment effects with 95% confidence intervals. Standard errors are clustered at the household and date levels to adjust for serial correlation. As clearly illustrated, the treated households significantly reduced their electricity consumption during peak hours. A more interesting phenomenon is that they reduced their electricity consumption in hours leading up to and following the peak rate period, during which the applicable unit rate was lower than the flat rate in the baseline period, even though most of the estimated treatment effects are statistically insignificant in those hours.

2.3.1.2 Hourly Average Treatment Effects in and near the Peak Rate Period

Estimating by-tariff-group ATEs in and near the peak rate period allows understanding how the relationship between the degree of change in household electricity consumption and the magnitude of a peak-demand-hour price increase evolves in and near the peak rate period.[24] To do so, I run the following regression for each of the four tariff groups:

$$kWh_{ith} \;=\; \beta_p \mathbb{1}\big[\text{Treatment \& Post}\big]_{it} \;+\; \alpha_{iw} \;+\; \gamma_{tw} \;+\; \delta_m \;+\; \epsilon_{ith} \qquad (2.2)$$

Excepting the dependent variable and the parameter of interest, the econometric model above is the same as (2.1). Specifically, the response variable kWh_{ith}, which means the electricity consumption by household i on the day t during the hour of the day h, is utilized due to its better accessibility in interpretation. The point estimates of β_p indicate the ATE for each of the three intervals included in rate period p. Table 2.3 summarizes the regression results.

[24] In this paper, the effects of four different information stimuli on household electricity consumption are not of interest. Pon (2017) studied the effects in detail using the same datasets.

The measured ATEs for the peak rate period re-confirm the finding provided in Prest (2020).[25] The table clearly shows that within-household aggregate demand for electricity during the peak rate period declined, with a significance level of 0.01, due to the deployment of TOU pricing. However, based on the point estimates for the four tariff groups, it is unclear whether an incremental change in peak-rate-period price increase induces a statistically meaningful additional change in household electricity consumption or not.

To quantify how residential consumers responded to the TOU program in off-peak hours close to the peak rate period, I also estimate ATEs in periods of two hours before and after the peak rate period (i.e., in pre- and post-peak periods). Interestingly, the table also demonstrates that in the pre- and post-peak periods, the implementation of the TOU tariff structures resulted in reductions in household electricity consumption, which are statistically different from zero, even though TOU prices were lower than the flat rate of 14.1 cents per kWh.[26] The reductions in both periods surrounding the peak hours suggest that the impact of the price increases in the peak rate period overtook the impact of the price drops in each off-peak period. Therefore, in the following empirical analysis, I will focus on linking household electricity consumption in the pre- and post-peak periods with the price increases in the peak rate period, instead of the price decreases in those off-peak periods.

[25] See Figure 6 in Prest (2020).

[26] Even insignificant point estimates (i.e., point estimates for Tariff Groups C and D in the pre-peak interval and Tariff Group C in the post-peak interval) have negative values.

Table 2.3: Hourly Average Treatment Effects in and near the Peak Rate Period

	Hourly Electricity Consumption (kWh/Hour)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙[Treatment & Post]	−0.125***	−0.161***	−0.119***	−0.249***	−0.032***	−0.143***	−0.058***
	(0.020)	(0.036)	(0.022)	(0.044)	(0.011)	(0.015)	(0.015)
	[−0.165, −0.085]	[−0.231, −0.090]	[−0.163, −0.076]	[−0.336, −0.163]	[−0.055, −0.010]	[−0.173, −0.114]	[−0.087, −0.029]
Description of Period	Peak	Peak	Peak	Peak	Pre-Peak	Peak	Post-Peak
Period of Hours	17 to 18	17 to 18	17 to 18	17 to 18	15 to 16	17 to 18	19 to 20
Tariff Group	A	B	C	D	All	All	All
Price Change in the Peak Rate Period	+6	+12	+18	+24	[-]	[-]	[-]
FEs: Household by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs: Month of Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	506,540	326,800	511,700	331,960	1,006,200	1,006,200	1,006,200
Adjusted R^2	0.384	0.397	0.383	0.367	0.308	0.379	0.372

Note: This table shows the results of the regression in Equation (2.2). The first four columns demonstrate the result for each of the four tariff groups in the peak rate period. The last three columns provide the result of all four tariff groups for each of the three periods. Standard errors in parentheses are clustered at the household and day of experiment levels to correct for serial correlation. The ranges in brackets are the 95% confidence intervals; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

2.3.2 Breakdown of Household Responses to Time-Of-Use Electricity Pricing

2.3.2.1 Breakdown of Household Responses in and near the Peak Rate Period

Figure 2.6 indicates the limitations of focusing on aggregate electricity consumption, as many studies have been doing. The figure clearly shows that aggregate household electricity consumption increases as the weather becomes colder in Ireland. Intuitively, the negative correlation between them can be mainly attributable to for-heating electricity consumption, which strongly depends on outdoor temperatures. It is a fact that aggregate residential electricity consumption also includes another type of electricity consumption: electricity consumption that is irrelevant to temperature variation, such as consumption for lighting. Those two broad categories of electricity consumption could react differently to TOU electricity pricing. Electricity consumption for heating can be transferred to a different time of the day (e.g., from 6 p.m. to 4 p.m. to avoid a higher unit price under the TOU tariff structures). On the other hand, electricity consumption for lighting is time sensitive. Due to the difference in the costs of relocating or changing electricity consumption, it is possible that the two channels of household electricity consumption respond to TOU electricity pricing in different ways. Therefore, using aggregate electricity consumption to examine households' responses to the time-varying price scheme enables me to access only the aggregated response.

Considering the discussion above, I decompose household electricity consumption into two broad categories—non-temp.-control-driven and temp.-control-driven electricity consumption—and examine how each category of electricity consumption responds to the introduction of the TOU tariff structures. The temperature-control-related electricity consumption here means using electricity to satisfy home heating needs (e.g., to warm up space or water). So, the use of electricity for heating strictly depends on each day's weather conditions, especially temperatures. Naturally, the non-temperature-control-associated electricity consumption makes up the rest.

I exploit daily Heating Degree Days (HDDs), which imply overall heating needs on a given day, to isolate the temperature-control-driven consumption from aggregate household electricity consumption. Because only aggregate metering data is available from the CER experiment dataset, there is no clue allowing me to classify household electricity consumption into two distinct categories in the dataset. To address this challenge, I presume that the portion of household electricity consumption that fluctuates according to daily HDDs is temperature-control-driven electricity consumption. Therefore, the electricity consumption for temperature-control use is

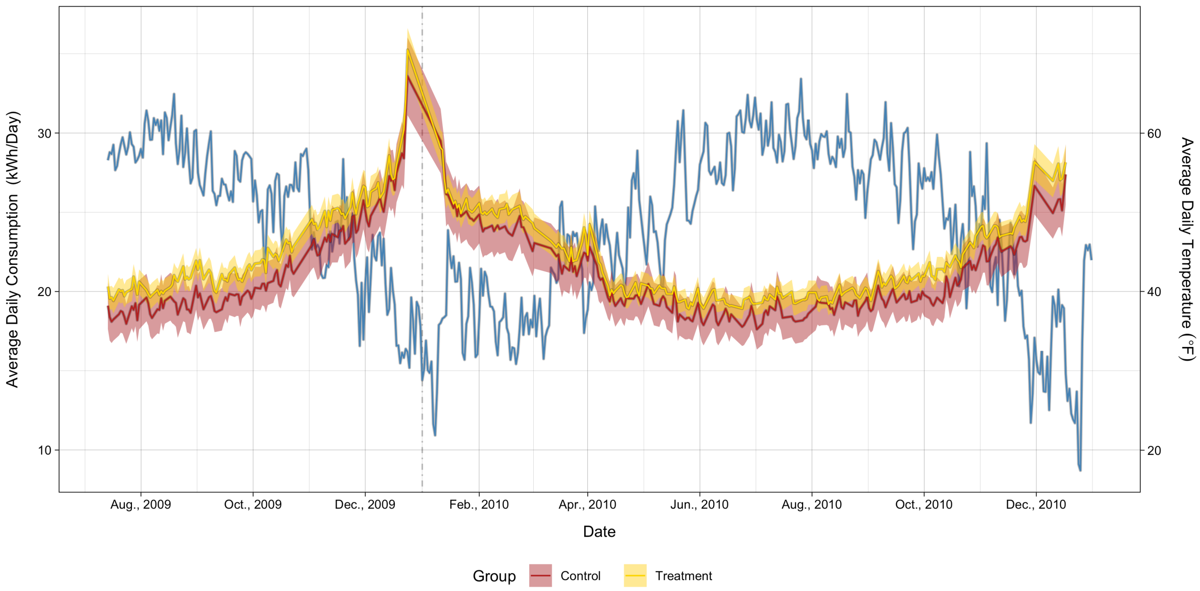

Figure 2.6: Average Daily Electricity Consumption

Note: The figure depicts, for households that exploit non-electric energy sources for their space and water heating, not only the average daily electricity consumption with 95% confidence intervals for each group (red and yellow lines) but also the mean daily temperature (blue line). From this figure, it is apparent that household daily electricity consumption is negatively correlated with the average daily temperature. In other words, in Ireland, outdoor temperatures are a crucial driver of within-household electricity consumption.

additional consumption that appears only on days with non-zero daily HDDs due to household heating needs.

To break down household responses to the TOU program around the peak rate period, I exploit the following DID-style spline regression model:[27]:

$$\begin{aligned} kWh_{ith} \;=\; & \beta_1 HDD_t \;+\; \beta_2 HDD_t^* \\ & + \big(\beta_3 \;+\; \beta_4 HDD_t \;+\; \beta_5 HDD_t^*\big)\mathbb{1}[\text{Treatment}]_i \\ & + \big(\beta_6 \;+\; \beta_7 HDD_t \;+\; \beta_8 HDD_t^*\big)\mathbb{1}[\text{Post}]_t \\ & + \big(\beta_9 \;+\; \beta_{10} HDD_t \;+\; \beta_{11} HDD_t^*\big)\mathbb{1}[\text{Treatment \& Post}]_{it} \;+\; \kappa_{dw} \;+\; \epsilon_{ith} \end{aligned} \tag{2.3}$$

Like (2.2), the dependent variable kWh_{ith} is the electricity consumption by household i on the day t during the hour of the day h. In this model, the full set of fixed effects in (2.2) has been superseded by two indicator variables—the first indicator variable $\mathbb{1}[\text{Treatment}]_i$ has the value of 1 if household i is assigned to the treatment group, and the second indicator

[27]The control group's less percentage changes on freezing days, which are illustrated in Figure (2.4) substantiate the use of the DID-style spline regression model in 2.3.

variable $\mathbb{1}[\text{Post}]_t$ equals 1 when the day t is in the treatment period. Although using the fixed effects as in (2.2) does not affect the treatment effects of interests, which is expected given the randomization, replacing them with the indicator variables allows for the interpretation of the average consumption by the treatment group to be more straightforward.[28] The model also includes interaction terms between HDD-relevant terms and those indicator variables. In the econometric model, HDD_t means the daily heating degree days on the day t. And HDD_t^*, which is required to introduce nonlinearity in HDD-associated response to TOU pricing, is mathematically defined as follows:

$$HDD_t^* \;=\; (HDD_t - Knot) \;\times\; \mathbb{1}[HDD_t > Knot], \tag{2.4}$$

where $Knot$ is a reference value at which the slope of the predicted line starts to change. For $Knot$, I utilize the value of ten in the following regression analysis because the median values of daily HDDs in the baseline and treatment periods are ten. The term κ_{dw} is day-of-week-by-half-hourly-time-window fixed effects.

The primary coefficients of interest in (2.3) are β_9, β_{10}, and β_{11}. The three coefficients show how much electricity consumption changes in the households assigned to the treatment group changed after implementing the TOU program compared to those in the control group. To be specific, β_9 demonstrates the change in residential electricity consumption for non-temperature-control use. Both β_{10} and β_{11} collectively represent the change in the amount of electricity consumed to meet household heating needs at given daily HDDs.

Using the point estimates of the three coefficients of interest provided in Table 2.4, I graphically summarize the predicted change in each of the two channels of electricity consumption in Figure 2.7. Regarding the change in electricity consumption for non-temperature-control use, the table and figure clearly show that the treated households significantly reduced their consumption when subject to peak-hour prices (i.e., in the peak rate period). Their non-temperature-control-driven electricity consumption also decreased in the pre- and post-peak periods, albeit noisy and relatively smaller in magnitude than the peak-hour changes.

[28]Added indicator variables instead of various fixed effects also enables an easier graphical summary of the regression results.

Table 2.4: Breakdown of Hourly Average Treatment Effects

	Hourly Electricity Consumption (kWh/Hour)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}$[Treatment & Post]	−0.017	−0.092***	−0.022	−0.057*	−0.127***	−0.078**	−0.189***
	(0.020)	(0.025)	(0.024)	(0.030)	(0.039)	(0.031)	(0.041)
$\mathbb{1}$[Treatment & Post] × HDDs	0.00005	−0.007**	−0.002	−0.010***	−0.002	−0.004	−0.009
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.006)
$\mathbb{1}$[Treatment & Post] × HDDs*	−0.002	0.008***	0.006*	0.013***	0.003	0.005	0.011*
	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)	(0.006)
Description of Period	Pre-Peak	Peak	Post-Peak	Peak	Peak	Peak	Peak
Period of Hours	15 to 16	17 to 18	19 to 20	17 to 18	17 to 18	17 to 18	17 to 18
Tariff Group	All	All	All	A	B	C	D
Price Change in the Peak Rate Period	[-]	[-]	[-]	+6	+12	+18	+24
Knot	10	10	10	10	10	10	10
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,006,200	1,006,200	1,006,200	506,540	326,800	511,700	331,960
Adjusted R^2	0.024	0.047	0.040	0.046	0.044	0.044	0.045

Note: This table shows the results of the regression in Equation (2.3). Only coefficients of interest are presented in the table. See Table A.6 to look at the full results. The first three columns provide the result of all four tariff groups for each of the three periods. The last four columns demonstrate the result for each of the four tariff groups in the peak rate period. Standard errors in parentheses are clustered at the household and day of experiment levels to correct for serial correlation; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

The change in temperature-control-associated electricity consumption occurred as well in all three two-hour periods, but its evolving pattern over daily HDDs was quite different in each period. Specifically, the impact of TOU pricing on residential electricity consumption for heating was U-shaped in the peak rate period. In contrast, in the hours before and after the peak period, the TOU intervention altered the electricity use for heating only on the coldest days (i.e., only when daily HDDs were sufficiently large). In other words, from the figure, it is evident that the change originating from temperature-control-related electricity consumption was a nonlinear function of daily HDDs in all three periods.

Specification (2.3) is also utilized to examine, for the peak rate period, the relationship between the degree of a price increase in that period and the change in electricity consumption. The by-tariff-group estimates of the coefficients of interest are also presented in Table 2.4. As shown in the table, on the whole, the reduction stemming from electricity demand for non-temperature-control use tends to be proportional to the size of price growth in peak hours, even though the point estimate for Tariff Group C is an exception. Therefore, the marginally diminishing effects of TOU pricing, discussed in Prest (2020), seem not to be championed by my point estimates. To be specific, while the aggregate electricity consumption during the peak rate period does not sensibly respond to incremental changes in the peak-hour price, the amount of electricity used for non-temperature-control purposes in the peak rate period does respond meaningfully to the marginal changes in the peak price. And the two estimates associated with temperature-control-driven electricity consumption (i.e., $\hat{\beta}_{10}$ and $\hat{\beta}_{11}$) are statistically significant only for the case of the smallest price increase (i.e., only for Tariff Group A).[29]

Altogether, those results imply two interesting points. First, the two distinct types of electricity consumption showed widely different responses to TOU prices in all three periods of two hours. Second, the measured reductions in non-temperature-control-related electricity consumption seem highly sensitive to the magnitude of a price increase in the peak rate period. Inspired by those implications, I formulate the resulting variations in household electricity consumption as a linear function of the magnitude of a rate change in peak-demand hours in the following section.

[29] In case of Tariff Group D, only $\hat{\beta}_{11}$ is statistically significant.

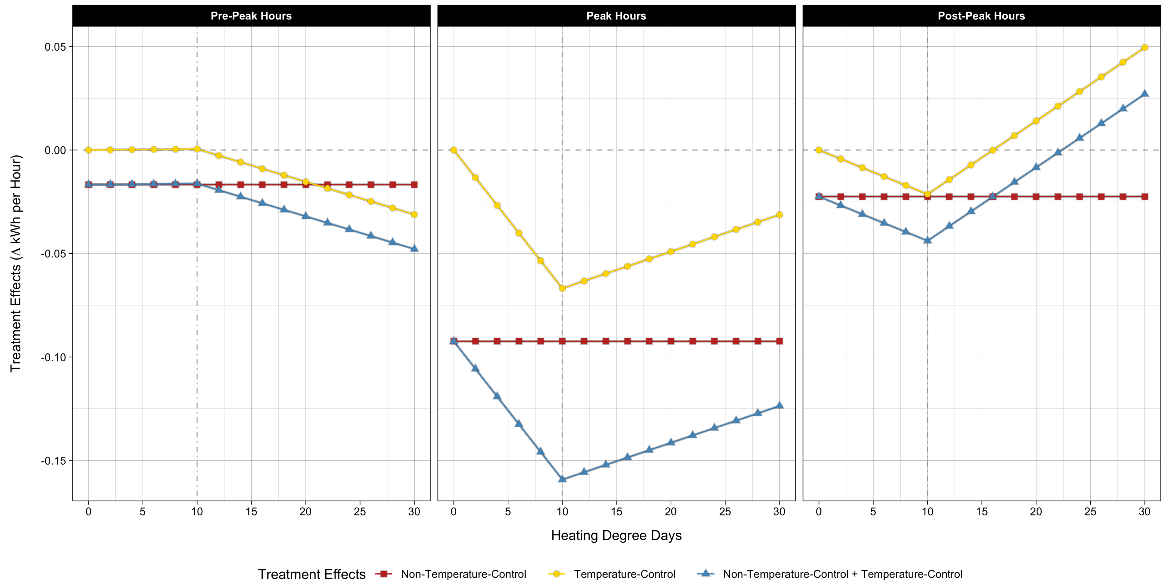

Figure 2.7: Breakdown of Hourly Average Treatment Effects

Note: This figure is a graphical summary of the regression results in the first three columns of Table 2.4. The order of panes corresponds to that of columns. As clearly illustrated, each two-hour interval shows distinct evolving patterns of two broad categories of household electricity consumption. The changes in non-temperature-control-driven household electricity consumption are straight lines because they are independent of outdoor temperature variation. On the other hand, the changes in temperature-control-associated residential electricity consumption are a nonlinear function of daily HDDs.

2.3.2.2 Household Responses as a Linear Function of Price Changes

To fully understand how residential consumers adjust their consumption behavior in response to price changes under the TOU program, it is necessary to explicitly examine the relationship between the size of the price changes and the change in each of the two distinct categories of household electricity consumption for each of the three periods (i.e., the pre-peak, peak, and post-peak periods). In other words, quantifying the impact of the marginal price change on residential electricity consumption will help evaluate the role of the intraday price variation under TOU electricity pricing. In the analysis, I utilize the magnitude of the price changes, from the flat rate, in the peak rate period for all three periods. There are two reasons why I exploit the price increases in the peak rate period rather than those in the corresponding period. One reason is that in the pre- and post-peak periods, the estimated changes in household electricity consumption do not show any apparent correlation with the price decreases in the corresponding periods.[30] The other reason is that the price changes in the peak rate period well encapsulate two different price incentives under TOU pricing in off-peak hours, price incentives for load-shedding and load-shifting.[31] Using the following econometric model, I quantitatively determine the relationship:

$$
\begin{aligned}
kWh_{ith} \;=\; & \beta_1 HDD_t \;+\; \beta_2 HDD_t^{*} \\
& + \;(\beta_3 \;+\; \beta_4 HDD_t \;+\; \beta_5 HDD_t^{*})\,\mathbb{1}[\text{Treatment}]_i \\
& + \;(\beta_6 \;+\; \beta_7 HDD_t \;+\; \beta_8 HDD_t^{*})\,\mathbb{1}[\text{Treatment}]_i \Delta PC_i \\
& + \;(\beta_9 \;+\; \beta_{10} HDD_t \;+\; \beta_{11} HDD_t^{*})\,\mathbb{1}[\text{Post}]_t \\
& + \;(\beta_{12} \;+\; \beta_{13} HDD_t \;+\; \beta_{14} HDD_t^{*})\,\mathbb{1}[\text{Treatment \& Post}]_{it} \\
& + \;(\beta_{15} \;+\; \beta_{16} HDD_t \;+\; \beta_{17} HDD_t^{*})\,\mathbb{1}[\text{Treatment \& Post}]_i \Delta PC_i \;+\; \kappa_{dw} \;+\; \epsilon_{ith}
\end{aligned}
\tag{2.5}
$$

The model is the same with (2.3) except for interaction terms between treatment-status-relevant indicator variables (i.e., $\mathbb{1}[\text{Treatment}]_i$ and $\mathbb{1}[\text{Treatment \& Post}]_{it}$) and ΔPC_i, where ΔPC_i is the difference between the peak-hour prices in the treatment period and the flat rate in the baseline period. The coefficients of the second interaction term (i.e., β_{15}, β_{16}, and β_{17}) capture the impacts of deploying TOU tariffs on household electricity consumption as a linear function of the degree of a peak-demand-hour price change.

The estimates of the six coefficients of interest (i.e., from β_{12} to β_{17}) are summarized graphically in Figure 2.8, which is extensively exploited throughout this paper. And this figure, showing the estimated treatment effects for the two consumption channels and the sum of the treatment effects in each of the three intervals, re-confirms the finding of peak-rate-period price increases' diminishing returns in Prest (2020).

In the peak rate period, the reduction in non-temperature-control-associated electricity consumption increased as the magnitude of a peak-hour price increase grew (see the panel in the first row of the second column of Figure 2.8). On the contrary, at given daily HDDs, the reduction in temperature-control-related electricity consumption weakly moved towards zero as the size of a peak-demand-hour tariff escalation increased (see the panel in the second row of the second column of Figure 2.8). As well illustrated in the panel in the third row of the second column of Figure 2.8, for a given value of daily HDDs, the differences in treatment effect across the level of price growth are seemingly dampened when the estimated treatment effects from two distinct categories of electricity consumption are aggregated due to the opposite response to peak-hour

[30] As discussed in the previous section, the price increases in the peak rate period clearly drive the changes in the two types of electricity consumption in the same period.

[31] Before and after the peak period, the two price incentives are proportional to the magnitude of the price increases in the peak period.

Table 2.5: Hourly Treatment Effects as a Linear Function of Peak-rate-period Price Changes

	Hourly Electricity Consumption (kWh/Hour)		
	(1)	(2)	(3)
$\mathbb{1}$[Treatment & Post]	−0.045	−0.028	−0.053
	(0.029)	(0.035)	(0.035)
$\mathbb{1}$[Treatment & Post] × ΔPC	0.002	−0.005**	0.002
	(0.002)	(0.002)	(0.002)
$\mathbb{1}$[Treatment & Post] × HDDs	−0.0001	−0.010**	−0.001
	(0.004)	(0.004)	(0.004)
$\mathbb{1}$[Treatment & Post] × HDDs*	0.001	0.012**	0.005
	(0.005)	(0.006)	(0.005)
$\mathbb{1}$[Treatment & Post] × HDDs × ΔPC	0.00001	0.0002	−0.0001
	(0.0002)	(0.0002)	(0.0003)
$\mathbb{1}$[Treatment & Post] × HDDs* × ΔPC	−0.0002	−0.0003	0.00004
	(0.0003)	(0.0003)	(0.0003)
Description of Period	Pre-Peak	Peak	Post-Peak
Period of Hours	15 to 16	17 to 18	19 to 20
Knot	10	10	10
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes
Observations	1,006,200	1,006,200	1,006,200
Adjusted R^2	0.024	0.047	0.040

Note: This table shows the results of the regression in Equation (2.5). Only coefficients of interest are presented in the table. See Table A.7 to look at the full results. Standard errors in parentheses are clustered at the household and day of experiment levels to correct for serial correlation; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

price increases in the two consumption categories.[32] Indeed, this empirical result is consistent with the finding discussed in the paper that a higher price results in a larger diminution in electricity demand, while additional gains diminish in the peak interval.

In the two-hour interval before the peak rate period, the two types of residential electricity consumption continue to respond differently to the peak price for given daily HDDs, but the pattern is now switched. The pre-peak period exhibits a more significant reduction in non-

[32]The last row of Figure 2.8 shows the sum of the first and second rows.

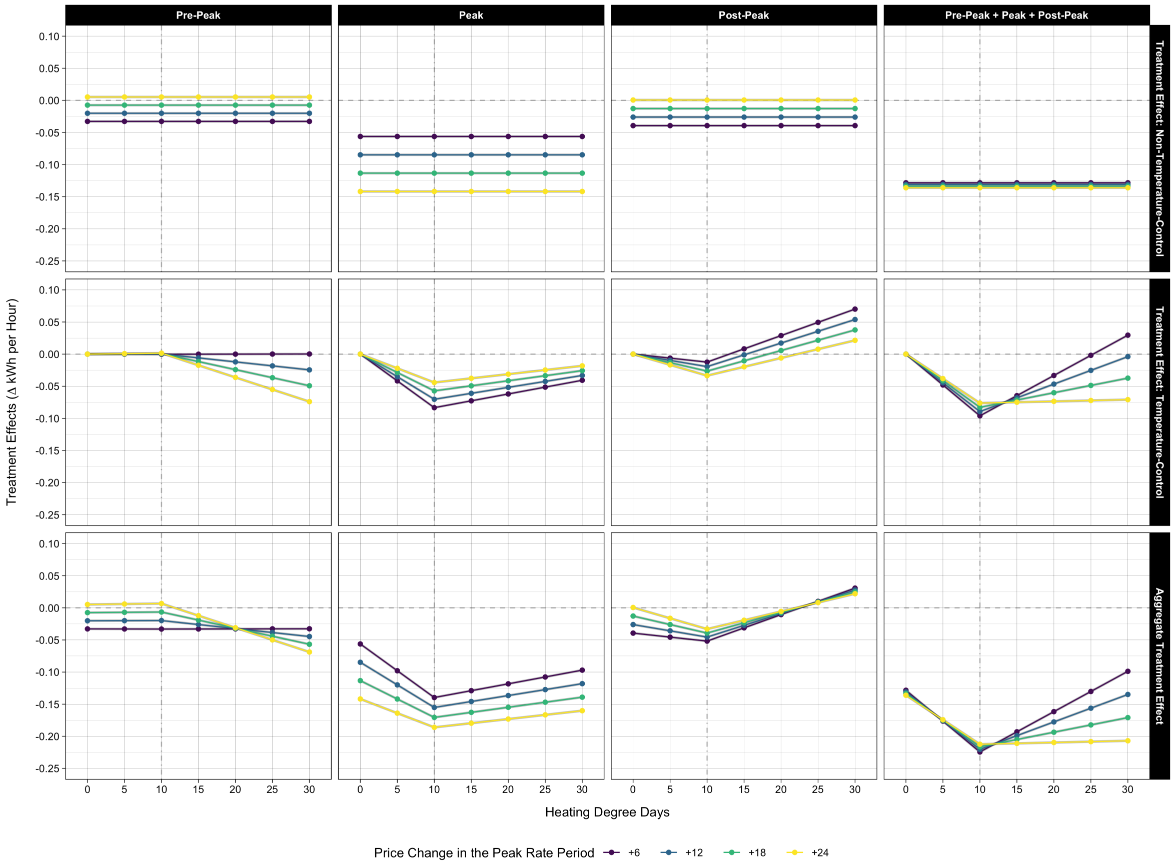

Figure 2.8: Treatment Effects as a Linear Function of Peak-hour Price Changes

Note: This figure depicts, for four different price changes in the peak rate period, estimated treatment effects as a linear function of price changes. The first row in the figure shows the treatment effects on non-temperature-control-driven household electricity consumption. The treatment effects on temperature-control-related residential electricity consumption are illustrated in the second row. The aggregate effects are presented in the last row. The first three columns correspond to the three two-hour periods (i.e., pre-peak, peak, and post-peak periods). The fourth column demonstrates the total changes in the three periods.

temperature-control-driven electricity consumption for a more minor change in peak-hour price (see the panel in the first row of the first column of Figure 2.8). By contrast, the larger the magnitude of a peak-rate-period price change, the wider the diminution in temperature-control-related electricity consumption during the pre-peak period (see the panel in the second row of the first column of Figure 2.8). For the same reason as in the peak period, the aggregate treatment effects of the TOU tariffs described in the last row of the first column of Figure 2.8 are seemingly less sensitive to peak-hour prices. Note that regarding electricity consumption for heating during the pre-peak period, TOU electricity pricing played a role only when household heating needs were sufficiently high.

Irish residential consumers adjusted their electricity consumption behavior during the post-peak period as well. As in the pre-peak period, consumption changes stemming from non-temperature-control-related electricity use increased as the size of a peak-demand-hour rate change diminished (see the panel in the first row of the third column of Figure 2.8). The TOU-price-induced change in temperature-control-driven electricity consumption evolved over daily HDDs somewhat complicatedly. Though depending on the magnitude of a peak-hour price increase, TOU tariffs reduced household electricity consumption for heating on Ireland's typical winter days in that period. Interestingly, the CER TOU program provoked additional heating-related consumption during the post-peak period on extremely cold days in Ireland. In addition, as the level of peak-demand-hour price alteration grew, the profile of measured treatment effect for temperature-control-associated consumption moved downward. Consequently, a higher price increase in the peak rate period resulted in a more significant reduction in electricity consumption for heating when heating demands were lower, while a smaller addition to electricity consumption for heating on cold winter days (see the panel in the second row of the third column of Figure 2.8). Altogether, as shown in the last row of the third column of Figure 2.8, the aggregate treatment effects of the TOU program in the post-peak period are superficially moderated because of households' opposite responses to peak-demand-hour price increases in the two distinct channels of electricity consumption.

In summary, under TOU electricity pricing, the degree of a price change in peak-demand hours, not just its existence, still matters to residential consumers' electricity consumption. The empirical results above suggest that the opposite directional changes in the two channels of electricity consumption make Irish households appear insensitive to the time-varying price structure. In other words, their high sensitivity to TOU prices is revealed only when their electricity consumption is disaggregated. Together with the empirical findings in previous sections, the results imply that three simultaneously interacting factors govern the dynamics of residential electricity consumption under TOU pricing: the timing when electricity is consumed, daily HDDs, and the magnitude of price increase in the peak rate period.

2.3.3 Dynamics of Household Electricity Consumption under Time-Of-Use Electricity Pricing

The preceding results from my empirical analysis highlight that households were quite responsive to incremental changes in the peak-demand-hour price. As the peak-hour price increased compared to the flat rate, non-temperature-control-related electricity consumption continued to decline in the peak rate period. In contrast, temperature-control-driven consumption did indeed fall, but these reductions in residential electricity consumption occurred outside of the peak rate period (i.e., in the pre- and post-peak periods). In this section, I will further examine what can drive these different patterns in the responses to TOU prices.

2.3.3.1 Mechanism: Load-shedding vs. Load-shifting

Examining participating households' electricity consumption, following a time sequence from the pre-peak to the post-peak period, facilitates a complete understanding of how they adapted to the TOU tariff structures in the CER experiment. Intuitively, residential consumers can respond to TOU tariffs by conserving their electricity consumption during the peak-demand hours, leading to an overall reduction in their demand for electricity. Instead of reducing their electricity consumption, they can shift it to off-peak hours so as not to be subject to the peak rate as much as possible. In this case, the level of their net electricity consumption in a day is maintained. Of course, those two ways of responding to time-varying price structures can co-occur. Because those two ways reshape load curves not only in the peak rate period but also in the hours surrounding that period, it will be natural to examine the impact of the TOU program on household electricity consumption from a time-moving perspective in order to grasp the whole dynamics of households' behavioral changes. In the following paragraphs, I will provide interpretations of the changes in households' consumption behavior, which are observed in my empirical analysis.

Regarding residential electricity demand for non-temperature-control uses, the leading reaction of the treated households to the TOU tariffs was to reduce their consumption in and near the peak rate period. According to my regression results summarized in Figure 2.8, in the peak rate period, the reduction in non-temperature-control-related electricity consumption increased as the magnitude of the price change in that period under the TOU program grew. Non-temperature-control-driven electricity consumption in the pre- and post-peak periods showed a weak but opposite variation—i.e., the reduction originating from households' non-for-heating consumption moved towards zero as the degree of the price increase in the peak rate period became larger. In the case of Tariff Group A, although there was almost zero price variation relative to the flat rate (i.e., only 0.1 cents per kWh) in the pre- and post-peak periods, the amount of the diminution in non-temperature-control-related electricity consumption for that group was nearly the same in all three periods. Meanwhile, despite more sizable price decreases, the remaining tariff groups also conserved, or at least sustained, their consumption for non-temperature-control uses in both surrounding periods. In other words, my empirical results reveal that reductions in households' non-for-heating electricity consumption spilled over into non-peak periods (i.e., the pre- and post-peak periods).

A remarkable point with respect to the spillovers to non-peak hours, suggesting households' behavioral changes related to non-temperature-control-driven electricity consumption in the pre- and post-peak periods, is that they seemed to relocate a part of their not-for-heating electricity consumption during peak hours to those two periods. As described in Figure 2.1, there were price drops in the hours before and after the peak rate period. Furthermore, for marginal electricity consumption, because the tariff group that paid the highest price in the peak rate period (i.e., Tariff Group D) paid the lowest price in the surrounding hours, the households in that group were more incentivized to move their peak-hour electricity consumption to off-peak hours. Hence, the phenomenon that the reduction in not-for-heating electricity consumption in the surrounding periods declined as the magnitude of the peak-rate-period price change increased is well explained by combining the load-shedding with the load-shifting, which was motivated by the monetary incentive from the price differences between the peak and off-peak periods. As shown in Figure 2.8, the relocation-associated consumption change, in general, did not fully outweigh the conservation-relevant one in both periods.

Taken together, with respect to non-temperature-control-driven electricity consumption, the households assigned to the treatment group responded to the TOU program via load-shedding as primary and load-shifting as secondary reactions. Interestingly, the total non-temperature-control-relevant reduction in and near the peak rate period, which is depicted in the fourth column of the first row in Figure 2.8, did not vary with the level of a peak-hour price increase. This outcome might reflect households' limited capability not only to identify possible sources of reducing their electricity consumption but also to realize lower consumption from the sources.

With respect to temperature-control-related household electricity consumption, Figure 2.8

depicts that the program caused a reduction in for-heating electricity use during the peak rate period, especially around typical values of daily HDDs during winter in Ireland.[33] Interestingly, although statistically insignificant, the smaller the magnitude of the peak-demand-hour price change increase, the larger the induced reduction in temperature-control-related consumption in the peak period. That is, the change in for-heating electricity consumption seems to violate the law of demand. As discussed above, the households assigned to Tariff Group D had the highest incentive to relocate their peak-hour electricity consumption to non-peak hours surrounding the peak-demand hours due to the largest across-period price difference. Therefore, the reduction in electricity consumption for heating in the pre-peak period, which occurred only on days with heavy heating needs, cannot be explained as a consequence of either the price decrease in that period or load-shifting. In other words, regarding temperature-control-driven household electricity consumption, as did in the peak rate period, the price signals did not function well in the pre-peak period. In the post-peak period, high daily HDDs incurred additional electricity consumption for heating after introducing TOU tariffs. The degree of the additional consumption, however, also cannot be justified by the price signals for the same reasons as in the pre-peak period.[34] And the amount of the additional consumption was generally not large enough to fully offset, for given heating needs in a day, the reduction in the preceding periods. In Section 2.3.3.2, I will discuss a possible explanation for the consumption behavior not backed by the price signals.

2.3.3.2 Household Electricity Consumption for Heating in a Time Line

From Figure 2.8, examining the curves that illustrate the change in temperature-control-associated electricity consumption for three consecutive periods simultaneously, but taking account of their time sequence, suggests a significant implication of the effectiveness of the TOU prices in the peak rate period. According to the figure, as the degree of peak-hour price escalation increased, the temperature-control-related consumption reduction in the pre-peak period expanded, while those in the peak period decreased gradually. Altogether, it is likely that a larger pre-adjustment leads to a smaller reduction in electricity demand for heating during peak-demand hours, which

[33] See Figure 2.3.

[34] The estimated changes in temperature-control-related electricity consumption with respect to peak-demand-hour price variation for the peak and post-peak periods, presented in Figure 2.8, seem rather to imply that the degree of load-shifting diminished as the financial incentive, measured by the price difference between the two periods, increased.

in turn seems to result in limited additional consumption during the following post-peak period. Compared to the case that a household does not reduce for-heating electricity consumption during the pre-peak period, consuming more for-heating electricity during peak hours seems necessary to prevent indoor temperatures from falling too much or persisting at a low level when the household significantly reduces its temperature-control-driven consumption during the pre-peak period.[35] In addition, the household will have less incentive to increase its electricity consumption for heating during post-peak hours since its room temperatures will be higher than if it were to reduce its electricity consumption for heating during peak hours considerably. In light of the fact that TOU tariffs are intended to conserve electricity consumption during peak-demand hours, it is reasonable to conclude that a lower reduction in peak hours due to a too large pre-adjustment results in a deterioration in the performance of the TOU tariffs.

As discussed in detail, under the TOU program, households' adjustments to their behavior for temperature-control-driven electricity consumption during the pre-peak hours seem to determine the degree of a reduction in that use of electricity during the following period (i.e., during the peak rate period) in lieu of price signals. In Figure 2.8, the gap in the temperature-control-related treatment effect at given daily HDDs between the lowest and the highest peak-hour rate changes, therefore, might be understood as potentially attainable gains when the pre-adjustments are suppressed. This explanation motivates the necessity of adopting home automation technologies, like Programmable Communicating Thermostats (PCTs), to restrict such adjustments only to the peak rate period. Considering the fact that households generally set a target temperature instead of micromanaging their heating devices according to ever-changing outdoor temperatures, PCTs with recommended default settings for temperature-control-associated use of electricity are highly likely to contribute to minimizing their behavioral changes prior to the peak rate period.[36] Moreover, the additional gains realized by utilizing the automated instruments provide legitimacy for the ongoing SEAI-offering Home Energy Grants, in which heating controls are an

[35]This interpretation is in line with the concept "discomfort" in Blonz et al. (2021). See Section 3.4 in the paper.

[36]Fowlie et al. (2021) examines default effects in a randomized controlled trial, in which the participants assigned to the control group defaulted into a residential electricity pricing program. Default effects have been studied in a range of settings, such as organ donation (Johnson and Goldstein, 2003; Abadie and Gay, 2006), car insurance (Johnson et al., 1993), and participation in retirement savings plans (Samuelson and Zeckhauser, 1988; Madrian and Shea, 2001; Choi et al., 2019).

essential part.[37]

2.4 An Alternative Electricity Pricing

2.4.1 Household Consumption Behavior over Daily Heating Degree Days

My empirical results obviously illustrate that the effectiveness of TOU tariffs, as measured by the amount of an induced reduction in household electricity consumption, nonlinearly varies with daily HDDs. As discussed, the alteration in electricity consumption caused by the deployment of TOU electricity pricing consists of two elements: the change in non-temperature-control-driven electricity consumption and that in temperature-control-driven electricity consumption. By definition, the change originating from non-temperature-control-related electricity consumption is independent of ever-changing weather conditions, including daily HDDs. Hence, the nonlinearity in the effectiveness of the TOU tariff structures, as illustrated in Figure 2.8, is utterly attributable to the other type of electricity consumption, that for heating.

The nonlinear relationship between the amount of change in temperature-control-associated electricity consumption and daily HDDs indicates an interesting characteristic of TOU pricing: the day-varying effect of TOU pricing on residential electricity consumption. Daily HDDs, one of the critical determinants of temperature-control-relevant electricity consumption, fluctuate day by day. Therefore, it is intuitive that in response to daily changing household heating needs, the TOU-price-induced change in electricity consumption for heating also alters every day.

The day-varying effectiveness of TOU electricity pricing suggests a significant implication in connection with Real-Time Pricing (RTP), a more granular time-varying electricity tariff structure.[38] Contrary to TOU pricing, rates typically change hourly under RTP. So compared to TOU pricing, RTP has an advantage in reflecting generation costs contemporaneously. In other words, RTP imposes a higher price in the situation that electricity demand is high, followed by high generation costs, to curb household electricity consumption. Economists, therefore, often advocate RTP over TOU pricing.

Because of the reduction in temperature-control-driven electricity consumption that covaries with daily HDDs, TOU electricity pricing can somewhat emulate the favorable feature of RTP

[37]Sustainable Energy Authority of Ireland (SEAI) is Ireland's national sustainable energy authority whose goal is to promote and assist the development of sustainable energy in Ireland. Detailed information about Home Energy Grants is available at https://www.seai.ie/grants/research-funding/.

[38]Harding and Sexton (2017) provides a detailed description of various kinds of time-varying electricity tariff structures.

on relatively warm winter days in Ireland—roughly speaking, on days when the value of daily HDDs is below ten. As evidently illustrated in Figure 2.6, households' heating needs drive the demand for electricity in Irish households. So, a more significant diminution in household electricity consumption is required on cold winter days to relieve the burden on the power grid. According to Figure 2.8, for example, for the households in Tariff Group A, the reduction in heating-associated electricity consumption in the peak rate period on warm winter days (i.e., on days when the value of daily HDDs fell between zero and ten), whose amount was more than half of the aggregated reduction in household electricity consumption under the TOU program at its maximum, expanded as households' heating needs became larger. This empirical finding means that comparing two warm winter days in Ireland, which have different values of daily HDDs, despite no across-day price variation under the price scheme, TOU electricity pricing induces a larger reduction in household electricity consumption during peak hours on the day with higher HDDs (i.e., on the day demonstrating higher generation costs due to more significant electricity demand). Consequently, in that case, the additional gains obtained by switching to RTP might not be as substantial as economists have expected. The excellent feature of TOU electricity pricing, however, gradually disappeared as daily HDDs grew above the value of ten, even though a more considerable reduction in household electricity consumption is required to ease the burden on the power grid.

2.4.2 Time-Of-Use Pricing with Additional Dynamics over Daily Heating Degree Days

The U-shaped curve of peak-demand-hour reduction in temperature-control-related electricity consumption is not a desirable feature of TOU electricity pricing. The fundamental intention of the time-varying tariff scheme is to reshape load profiles, especially in the peak rate period, in order to avoid excessive investment in power generation capacity. So a higher amount of reduction in electricity consumption for heating on freezing days (i.e., on days when the power grid is most burdened) serves the purpose of the price scheme. In light of that, the U-shaped evolving pattern over daily HDDs is unattractive because on days with high heating needs, TOU electricity pricing induces even less reduction in for-heating-relevant household electricity consumption.

An alternative electricity pricing scheme, a TOU-like tariff structure with additional flexibility in price variations across daily HDDs, could address the disadvantage of typical TOU pricing revealed from my analysis (i.e., less effectiveness on days with very low temperatures). My empirical findings illustrate two important points with respect to the relationship between TOU-tariff-induced changes in household electricity consumption and price increases during the peak rate period. First, the reduction stemming from non-temperature-control-associated electricity consumption becomes larger as the magnitude of a price escalation in the peak period increases. Second, the gains obtained by marginally raising the peak-hour electricity price (i.e., an additional reduction in non-temperature-control-relevant electricity consumption) exceed the losses from such a marginal increase (i.e., a fewer reduction in temperature-control-driven electricity consumption).[39] Those two points collectively imply that scaling up the size of a rate change in the peak rate period as daily HDDs rise enables achieving a more considerable TOU-price-induced aggregate reduction in residential electricity consumption.

Figure 2.9 depicts an alternative price scheme and additional gains from it. Under the price scheme proposed in the upper part of the figure, the peak-demand-hour price jumps as household heating needs become serious. To be specific, prior to the value of daily HDDs that typical TOU pricing becomes ineffective, the magnitude of peak-rate-period price change is evenly six cents per kWh. After that point, every time daily HDDs rise by five, the degree of peak-demand-hour price change increases by six cents per kWh.

The lower part of Figure 2.9 shows additional gains from the alternative pricing scheme, which are shaded with distinct colors for each six-cent escalation in peak-rate-period price. The five U-shaped profiles over daily HDDs, indicating the predicted reductions in household electricity consumption for five different price changes in the peak rate period, are drawn by utilizing the point estimates provided in Table 2.5. As illustrated in the figure, compared to the case in which the size of peak-hour price growth is fixed at six cents for all values of daily HDDs, the alternative price scheme can induce more significant reductions in household electricity consumption according to increasing household heating needs by synchronizing price increases in the peak rate period with daily HDDs. In other words, the weakness of typical TOU pricing can be alleviated under the proposed price structure.

The alternative price scheme is well in line with the key finding in Schittekatte et al. (2022). According to this recent paper, TOU rates complemented with Critical Peak Pricing (CPP) work well for reflecting spot-price-providing within-day load-shifting incentives. Considering

[39]See the three panels in the second column of Figure 2.8.

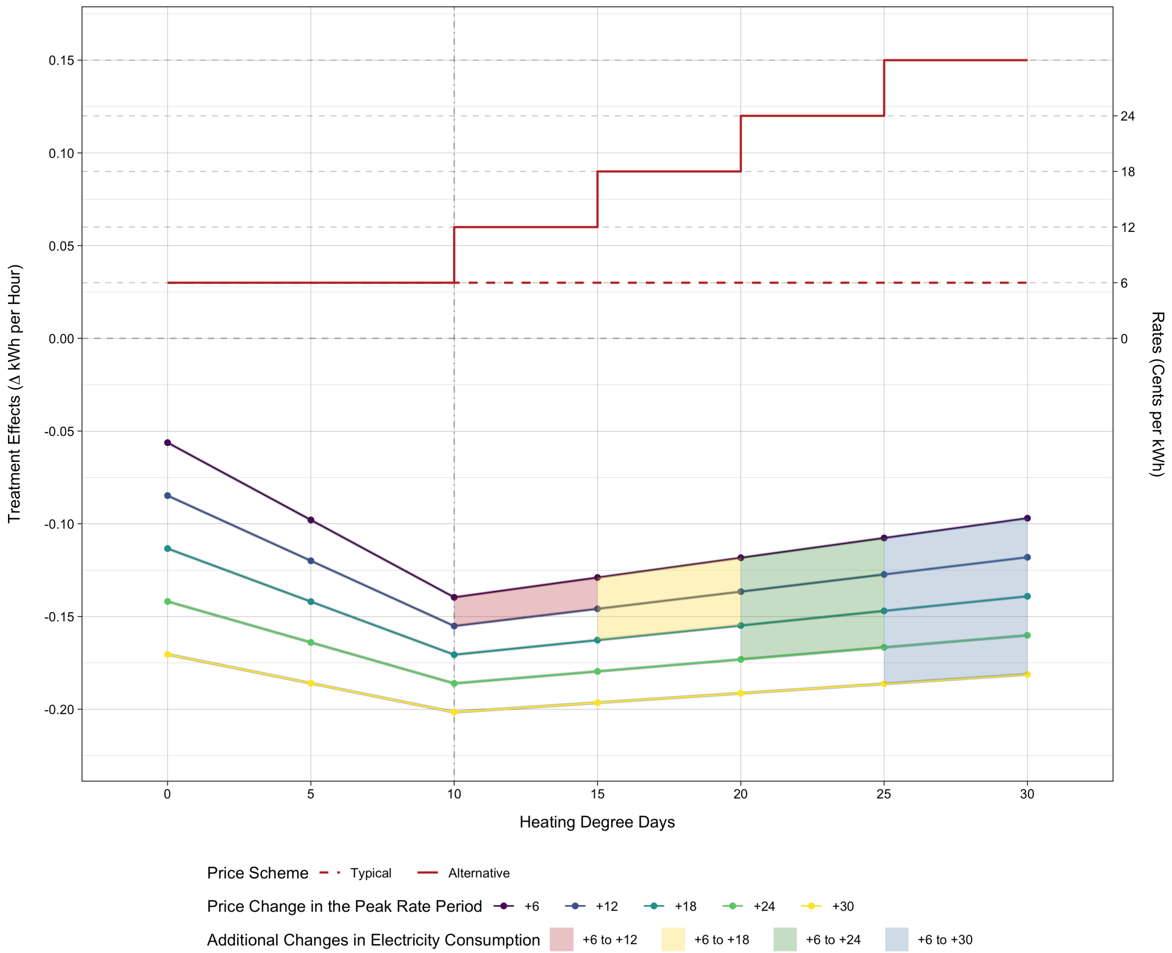

Figure 2.9: Additional Gains from an Alternative Electricity Pricing Scheme

Note: This figure illustrates two different price schemes. Under a typical TOU electricity pricing scheme, the rate in the peak rate period is 6 cents per kWh regardless of daily HDDs. On the contrary, under an alternative tariff structure that is TOU-style but has extra flexibility across daily HDDs, the peak-hour price escalates as household heating needs grow. The shaded areas depict additional gains obtained by adopting the redesigned pricing scheme, which are mainly attributable to more significant reductions in non-temperature-control-driven household electricity consumption.

that CPP introduces dramatic but short-lived price escalations when generating costs exceed a certain threshold infrequently, a very high peak price linked with exceptionally large daily HDDs in Ireland under the proposed alternative price scheme is consonant with CPP events with which TOU prices are complemented as suggested in the paper.

In addition, this proposed price structure is better than the typical TOU tariff structure with a higher fixed peak-demand-hour price. For example, Tariff Group D reduces household electricity consumption as much as the alternative price scheme on extremely cold days. However, compared to Tariff Group D, households under the proposed price structure can consume more electricity on warm days on which the power grid still has enough spare capacity to meet higher electricity demand.

2.5 Conclusion

The primary aim of various types of time-varying electricity pricing is to reshape load curves, especially around the peak-demand hours. Under the dynamic pricing of electricity, prices—more precisely, price variations—, which reflect instantaneous generation costs, are utilized to incentivize consumers to change their consumption behavior. Therefore, their responsiveness to the price changes in the tariff structures determines whether the time-varying electricity prices, including TOU pricing, will work as intended. In this paper, I quantify how sensitively households adjust their electricity consumption in response to TOU prices in and near the peak rate period. The results from my empirical analysis reveal two interesting points: household electricity consumption, consisting of two categories of electricity use—non-temperature-control-driven and temperature-control-driven consumption—, 1) sensitively responded to the magnitude of the price change in the peak rate period, and 2) also depended on daily heating degree days as well as the point electricity was consumed in time for a given rate change. In other words, my empirical analysis discloses the multidimensional dynamics of households' responses to the TOU tariffs.

Those findings provide important policy implications for TOU electricity pricing. First, along with residential consumers' high price sensitivity, the nonlinearity in their responses to daily heating needs proposes an alternative pricing scheme: TOU pricing with additional flexibility induced by synchronizing the magnitude of the peak-demand-hour price jump with daily heating degree days. Second, taking a close look at the relationship between the size of the peak-hour price increase and the changes in electricity consumption for temperature-control uses in chronological order emphasizes the importance of adopting home automation technologies, like Programmable Communicating Thermostats (PCTs), to improve the performance of TOU pricing.

My empirical findings and the policy implications derived from them ultimately indicate that an integrated understanding of the multidimensional dynamics of households' responses to TOU electricity pricing is required to make the price structure function with its full potential as a demand management tool. Furthermore, even for stakeholders in the electricity market, such as power generators, investors, regulators, and policymakers, comprehending how electricity consumption reacts to the time-varying pricing is critical because consumers' behavioral changes are an important piece of information in their decision makings.

Chapter 3

From Hotelling to DCDP Model: New Approach for Microeconomic Empirical Work in Oil and Gas Extraction

(Coauthored with Mark J. Agerton[1])

3.1 Introduction

Hotelling's model of exhaustible resource extraction provides simple but useful economic intuitions about the trade-off between extraction today and extraction in the future in the context of the forward-looking resource owners. The framework is flexible in applying to real-world resource extraction problems, such as exploration (Pindyck, 1978; Arrow and Chang, 1982; Swierzbinski and Mendelsohn, 1989; Quyen, 1991), uncertainty over reserves/demand/price (Gilbert, 1979; Pindyck, 1980, 1981; Farrow and Krautkraemer, 1989), taxation effects (Sweeney, 1977; Heaps, 1985), and technological improvement (Stiglitz, 1974; Slade, 1982). Accordingly, economists have utilized this canonical theory of the optimal depletion of nonrenewable resources for many decades to understand how exhaustible resource markets function. Hotelling's model, however, shows a different story in terms of empirical work. The main focus of the empirical literature on the Hotelling framework has been to test the well-known r-percent rule that a resource's shadow price has to rise at the rate of interest r. Unfortunately, such attempts have not been very fruitful due to various econometric issues and the fact that resource rents are generally

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unobservable.[2] Furthermore, recent empirical work on oil and gas extraction tends not to use Hotelling's theoretical model.[3]

Anderson, Kellogg and Salant (2018) (AKS) extends Hotelling's model by adding a new layer to oil producers' decision-making. AKS allows extractors to manipulate the rate of extraction from each well (the intensive margin) as well as the rate of drilling new wells (the extensive margin). The authors document several stylized facts about oil production: 1) oil production from existing wells is unresponsive to oil prices, which is inconsistent with Hotelling's classic model; however, 2) the rate of drilling is responsive to oil prices. The authors can reconcile these stylized facts with their reformulation of the Hotelling model.

Adding the heterogeneous geological features of different well sites is a natural augmentation to the AKS theoretical model. As discussed in Agerton (2020), variation in geological characteristics, which we denote *resource quality*, is a key driver of well-level productivity and firms' extraction decisions. We extend the AKS framework to incorporate heterogeneity in resource quality and well-level cost shocks. This extension has several benefits. First, we can accommodate what we see empirically in U.S. production—that firms develop high- and low-quality resources at the same time. Second, our specification is both analytically tractable, allowing for analysis with standard optimal control methods, as well as empirically tractable, allowing for econometric estimation.

To examine the validity of our extended model, we empirically analyze the resource quality of horizontal wells in North Dakota. As is well known, the geological quality of a given well site is usually observable only by extraction firms, though there are publicly available data that we can exploit to gauge it, such as the geological survey data published by the North Dakota Geological Survey (NDGS). Inspired by Herrnstadt, Kellogg and Lewis (2020), we use Robinson's partial linear model with detailed well-level data on horizontal wells drilled in North Dakota to estimate resource quality in each location. This estimation process provides us with

[2] See Gaudet (2007) and Thille and Slade (2009).

[3] Kellogg (2014) examines the relationship between drilling investments in Texas and oil price volatility. Fitzgerald (2015) studies experiential gains in hydraulic fracturing. Muehlenbachs, Spiller and Timmins (2015) investigates the impacts of shale gas development on the housing market. Boomhower (2019) examines the effects of bankruptcy protection on industry structure and environmental outcomes. Lewis (2019) studies the effects of a complex patchwork of mineral ownership on the oil and gas extraction outcomes. Using a government oil lease lottery, Brehm and Lewis (2021) shows that initial assignment results in different trade, drilling, and production outcomes.

two interesting stylized facts. One interesting fact is that fracking firms in North Dakota drilled well sites with different levels of resource quality simultaneously. The other empirical fact we discovered is that drilling of low-quality well locations decreased more than that of high-quality ones in response to the oil price drops during the second half of 2014.

The stylized facts from our analysis of the quality of drilled well sites in North Dakota raise two issues in modeling fracking firms' drilling activity based on the extended AKS framework. First, we find that the AKS-style model incorporating well sites' heterogeneous resource quality cannot rationalize the simultaneous drilling of well sites with different quality levels. Simply put, the model is not able to explain the empirical finding. Second, the simultaneous drilling of well locations with heterogeneous resource quality is inconsistent with the well-known least-cost-first extraction rule in exhaustible resource extraction. Holland (2003), which shows that limited extraction capacity causes the rule not to hold, seems to indicate that we need to include additional extraction-capacity-associated constraints that are highly sophisticated to model to make our extended model describe the empirical facts well. In this context, we suggest adopting a different approach to developing an economic model that enables us to explain fracking firms' drilling activity observed in North Dakota convincingly.

In this paper, following Arcidiacono et al. (2016), we develop a Discrete Choice Dynamic Programming (DCDP) framework in continuous time to model firms' drilling decisions. In this theoretical model, we formulate the decision to drill as an optimal stopping problem that trades off drilling a given well site today against drilling it at some time in the future. This trade-off is also the central idea of Hotelling's classic model. In our formulation, we introduce choice-specific cost shocks ϵ's that allow us to address the two problems we faced with respect to the extended AKS-style model. Because the cost shocks reflect a range of constraints that affect oil production companies' drilling decisions but are difficult to quantify by econometricians, they allow us to avoid adding various constraints to our model. Our model incorporating the cost shocks can also rationalize the empirical finding that fracking firms in North Dakota drilled horizontal wells with heterogenous quality simultaneously. Furthermore, under the assumption of a continuum of infinitesimally small well sites, our framework enables us to compute market-level drilling and production by aggregating the drilling decision for the marginal well location. In addition to its analytical tractability, one of the main advantages of the DCDP framework is that the model is estimable empirically using microeconomic data, which are available from both commercial and government databases.

We examine the equilibrium dynamics implied by our DCDP model in continuous time, especially focusing on how hydraulic fracking firms adjust their drilling, and thus oil production, in response to changes in oil prices under different conditions. First, we investigate the impact of unexpected demand shocks on the evolution of optimal drilling paths. Our simulation shows that a negative demand shock results in an immediate decrease in drilling, oil production, and the equilibrium oil price and that the equilibrium oil price gradually increases after the discontinuous drop. Second, we simulate how firms' drilling activity on well locations with heterogenous resource quality responds to unexpected price shocks. The time paths from this simulation demonstrate an interesting result that is consistent with our empirical observation: they reduced the drilling of low-quality well sites more than that of high-quality ones. Third, we compute the time paths of optimal drilling of horizontal wells and oil production from them under two distinct types of oil prices—exogenous and endogenous oil prices. The obtained equilibrium paths show that exogenous oil prices cause a higher drilling rate over the early period in our simulation.

The rest of this paper proceeds as follows. Section 3.2 discusses a set of data utilized for this research and the results from our empirical analysis. In Section 3.3, we develop a continuous-time DCDP model for drilling decisions in oil and gas extraction. Section 3.4 presents, under distinct conditions, the time paths of optimal drilling and oil production implied by our model, and Section 3.5 concludes.

3.2 Data and Empirical Analysis

3.2.1 Data

This section summarizes data on wells, geology, and oil prices, which are utilized to conduct empirical analysis and estimate a model of drilling behaviors observed in North Dakota.

3.2.1.1 Well Data

We scrape data for well in North Dakota's Bakken region from the data portal of the North Dakota Industrial Commission (NDIC), the regulator for the drilling and production of oil and gas in North Dakota.[4] NDIC-providing well data include a complete index of all wells permitted in North Dakota. The data contains basic information for each well, such as the type of well,

[4]NDIC's well data are available at Official Portal for North Dakota State Government.

Table 3.1: Summary Statistics for Wells

	Mean	(S.D.)	P25	P50	P75
Production					
Cumulative Oil Production (Bbls)	211,491.30	(108,012.00)	136,811.50	193,354.00	267,052.20
Cumulative Producing Days (Days)	1,451.37	(356.58)	1,343.75	1,601.00	1,697.00
Drilling					
Water (Bbls)	101,716.50	(249,157.50)	42,032.75	65,856.00	130,219.20
Sand/Proppants (Lbs)	4,553,380.00	(4,560,985.00)	2,312,951.00	3,441,914.00	5,543,660.00
Horizontal Drilling (Feet)	23,866.77	(15,134.08)	19,276.23	20,025.88	21,227.25
Geological Characteristics					
Thickness (Feet)	44.79	(13.48)	37.50	44.50	44.50
Thermal Maturity	0.64	(0.20)	0.50	0.50	0.75
Total Organic Content	13.62	(1.98)	12.24	13.34	15.13

Note: This table presents summary statistics for 694,294 horizontal wells whose cumulative production month equals or exceeds 24.

completion and spud dates, location, the first and the current operator names, and targeting pool. Individual well's production and injection histories, including producing days during each month, are also contained in the data.

Detailed well completion data are also obtained from the NDIC.[5] The data contain how much water and proppant were consumed during well simulations.

The regulatory body also provides well-level survey data. The survey data include detailed information on the path of each wellbore, including the direction and length of each lateral.

Throughout this paper, we use the sample of 24,520 horizontal wells that targeted the Bakken pool.[6] Summary statistics for those wells are presented in Table 3.1.

3.2.1.2 Geological Survey Data

We obtain geological survey data from the North Dakota Geological Survey (NDGS).[7] We follow Covert (2015) to match the three geological characteristics with each horizontal well in our sample.[8] Figure A.6 demonstrates the spatial distribution of well-level geological features.

[5]Using Form 6, Well Completion or Recompletion Report, filed by operators, the NDIC has developed the detailed data.

[6]According to Lee (2019), the Bakken pool includes Bakken, Three Forks, and Sanish formations.

[7]To be specific, we exploit NDGS maps GI-59 and GI-63.

[8]Refer to Section 2.4.1 of Covert (2015).

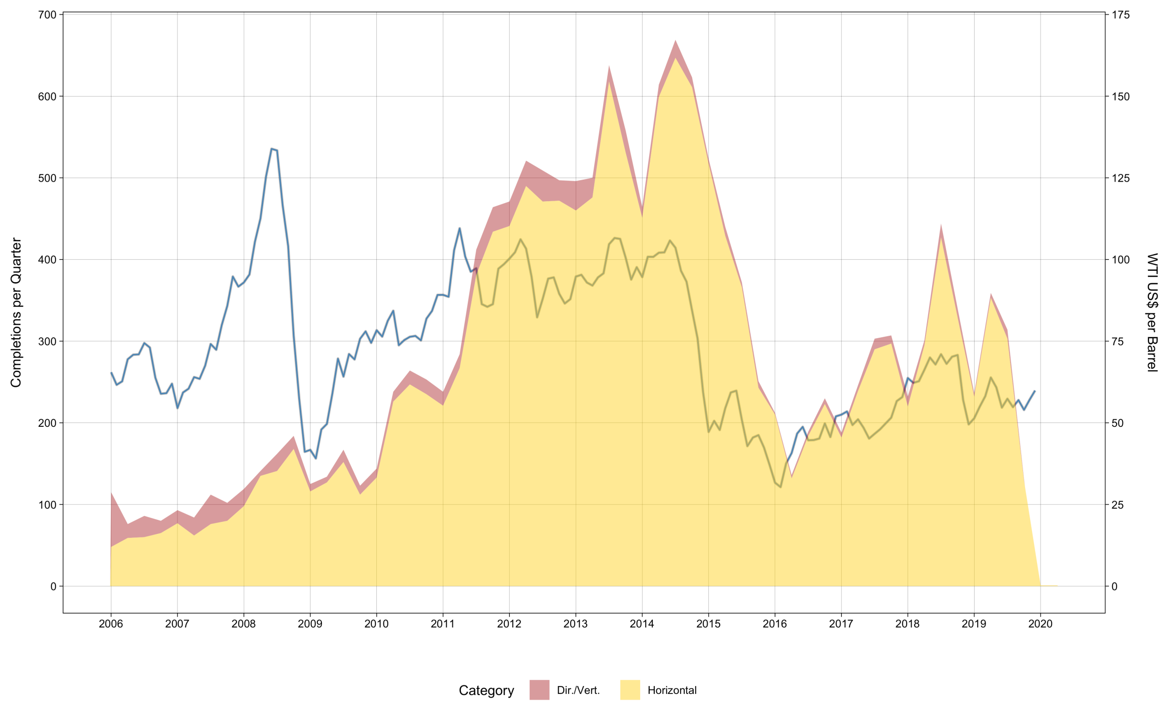

Figure 3.1: Time Series of the Number of Well Completions in North Dakota

Note: This figure shows the time series of the number of well completions in North Dakota. Horizontal wells have been strictly dominant in that area. The solid line in the figure is the monthly per-barrel spot prices for West Texas Intermediate at Cushing, Oklahoma. The figure suggests that the spot prices positively correlate with horizontal well completions in North Dakota.

3.2.1.3 Oil Price Data

We collect the monthly per-barrel spot prices for West Texas Intermediate at the Cushing, Oklahoma from the Energy Information Administration.[9] As shown in Figure 3.1, there was a striking movement in oil prices between 2014 and 2016. Specifically, oil prices, maintained at around \$100 per bbl during the first half of 2014, had continued to plunge, reaching less than \$50 per bbl in January 2015. After recovering to \$60 per bbl during the first half of 2015, oil prices had fallen to \$30 per bbl by the end of the year. Since then, oil prices have gradually risen until they declined again during the final quarter of 2018.

3.2.2 Empirical Analysis

3.2.2.1 Correlation between Oil Prices and Horizontal Drilling in North Dakota

Figure 3.1 shows how well completions in North Dakota evolved between 2009 and 2020. As clearly illustrated, well completions, which were driven mainly by horizontal wells, dramatically

[9] Time series data for Cushing, OK WTI Spot Price FOB is available here.

increased from the beginning of 2010.

According to the figure, it is evident that drilling horizontal wells in North Dakota is closely correlated with oil prices, especially after 2009. On the whole, oil prices significantly increased between 2009 and 2010 and remained high until mid-2014. Then, there was a sharp plunge in oil prices from mid-2014 to the end of 2015, and horizontal well drilling declined too. When oil prices gradually climbed between 2016 and 2020, North Dakota's drilling activities also recovered. To summarize, oil prices and the number of horizontal drilling in North Dakota seem to be positively correlated. Importantly, such a positive correlation between oil prices and horizontal drilling in the state suggests that fracking firms' drilling decisions strongly depend on oil prices. In Section 3.2.2.2, we show that their drilling decisions are linked with oil prices through the geological features of well sites.

3.2.2.2 The Role of Geological Quality in Horizontal Drilling

Estimation of Unobservable Geological Characteristics of Horizontal Wells — Not all well-specific information on geological features is available to econometricians. The NDGS geological survey data only include estimates of four different measurements of geological properties at a given location. Because the geospatial data was published to the public in 2008, it is likely that fracking firms, whose objective is to maximize their profits, have already exploited the contents of the maps. As discussed in Agerton (2020), learning about the spatial distribution of deposits by drilling wells is one of three economic factors that govern firms' where-to-drill decisions. So, it is reasonable to suppose that firms have private information about the Bakken area's spatial distribution of geological characteristics, which is not accessible to researchers.

The geological characteristics observed only by firms play two different roles in their drilling decisions. First, firms choose whether to drill a location based on its resource quality. Thus, the sample of wells we observe is not random: it has been selected based on unobservable (to us) resource quality. Second, firms' choice of inputs during hydraulic fracturing of each well may be correlated with the unobservable resource quality. For these reasons, accounting for resource quality is critical in modeling firms' decisions and production functions.

Following Herrnstadt, Kellogg and Lewis (2020), we employ Robinson's partially linear model to determine the unobservable quality of the horizontal wells completed between 2009 and 2018. We first specify the oil production from a horizontal well as

$$\log(y_i) \;=\; \log(\boldsymbol{X}_i)'\boldsymbol{\beta} \;-\; \lambda(longitude_i, latitude_i) \;+\; \epsilon_i. \tag{3.1}$$

In this specification, y_i are horizontal well i's cumulative oil production at its cumulative production month 24.[10] The covariate vector $\boldsymbol{X}_i$ for well i includes hydraulic fracturing inputs (i.e., fluid volume, proppant weight, and length of horizontal drilling), cumulative producing days, and observable geological characteristics (i.e., thickness, total organic contents, and thermal maturity). The term $\lambda(longitude_i, latitude_i)$ is a nonparametric function of each well's coordinates and captures well i's unobservable resource quality. Lastly, ϵ_i is a productivity shock not correlated with resource quality.

To operationalize model (3.1), we estimate the following partially linear model:

$$\log(y_i) \; - \; \widehat{m}_{y_i} \; = \; (\log(\boldsymbol{X}_i) \; - \; \widehat{\boldsymbol{m}}_{\boldsymbol{X}_i})' \boldsymbol{\beta} \; + \; \epsilon_i. \tag{3.2}$$

Here, $\widehat{m}_{y_i}$ are predictions from a non-parametric regression of $\log(y_i)$ on well i's coordinates $(longitude_i, latitude_i)$. The $\widehat{m}_{y_i}$ terms are smoothed means. Differencing these means out serves the same role as the within-transformation in a fixed effects model. In fact, if one used a uniform kernel function, $\widehat{m}_{y_i}$, within discrete cells, the estimator would be mathematically identical to fixed effect estimation with spatial fixed effects for each well. Predictions $\widehat{\boldsymbol{m}}_{\boldsymbol{X}_i}$ are obtained from different nonparametric regressions whose dependent and independent variables are $\log(\boldsymbol{X}_i)$ and $(longitude_i, latitude_i)$, respectively. The values of primary interest $\widehat{\lambda}_i$ (i.e., the unobservable geological quality of horizontal well i) are estimated as follows[11]:

$$\widehat{\lambda}_i \; = \; \widehat{m}_{y_i} \; - \; \widehat{\boldsymbol{m}}'_{\boldsymbol{X}_i} \widehat{\boldsymbol{\beta}} \tag{3.3}$$

In our analysis, we define low- and high-quality locations by dividing our sample of well sites into those with $\widehat{m}_{y_i}$ below and above the median. Even though $\widehat{m}_{y_i}$ is estimated from only higher-quality locations with observed drilling, and therefore biased upward, the ordinal ranking of well sites should be affected less. Figure A.5 shows the spatial distribution of the estimated quality.

Simultaneous Drilling of Horizontal Wells with Heterogeneous Geological Qualities — Figure 3.2, summarizing the estimated geological qualities of horizontal wells in scatter plots, clearly demonstrates that horizontal wells with a range of geological qualities were drilled simultaneously in the Bakken region of North Dakota. And as shown in Figure 3.3, simultaneous drilling is observed even at the firm level.

[10] That is, unobservable geological features are estimated cross-sectionally in our estimation.

[11] For details of Robinson's difference estimator, refer to *9.7.3 Partially Linear Model* in Cameron and Trivedi (2005).

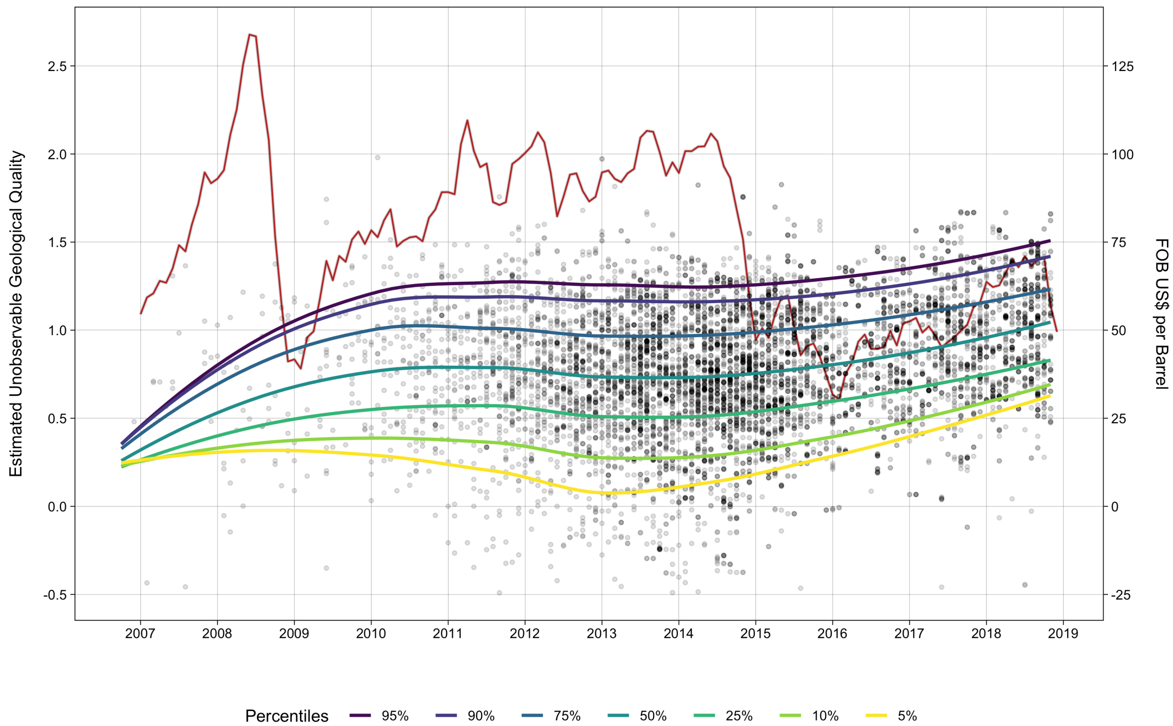

Figure 3.2: Simultaneous Drilling of Horizontal Wells with Heterogeneous Geological Quality

Note: This figure indicates the estimated geological feature for each horizontal well, depicted as a dot. Those dots definitely suggest the simultaneous drilling of horizontal wells with heterogeneous geological quality. In the figure, percentiles of the estimates, with the 95% confidence interval of each, are also presented. The solid red line is the time series of the monthly per-barrel spot prices for West Texas Intermediate at Cushing, Oklahoma. Oil prices plunged significantly between 2014 and 2015 and rose gradually. The percentile lines skewed upward, especially lower ones, as of the second half of 2014.

Simultaneous drilling of both low- and high-quality resources contradicts the well-known least-cost-first extraction rule in nonrenewable resource extraction.[12] According to the rule derived from the canonical Hotelling model, deposits of an exhaustible resource should be exploited in strict order, beginning with the lowest cost deposit.[13] Because a larger estimate of the unobservable geological quality implies higher ultimate oil production, if the rule holds, wells with larger estimates, thus having lower per-barrel marginal cost, should be first extracted. Those figures, however, do not show the theoretical prediction at all.

The High Sensitivity of Drilling Low-quality Horizontal Wells to Negative Price

[12]The cost that matters here is the marginal cost. And the marginal cost consists of two distinct costs: the marginal cost of drilling a new well and the marginal cost of extracting oil from existing wells.

[13]See *Selection 7 Depletion and Economic Theory* in Herfindahl and Brooks (2015).

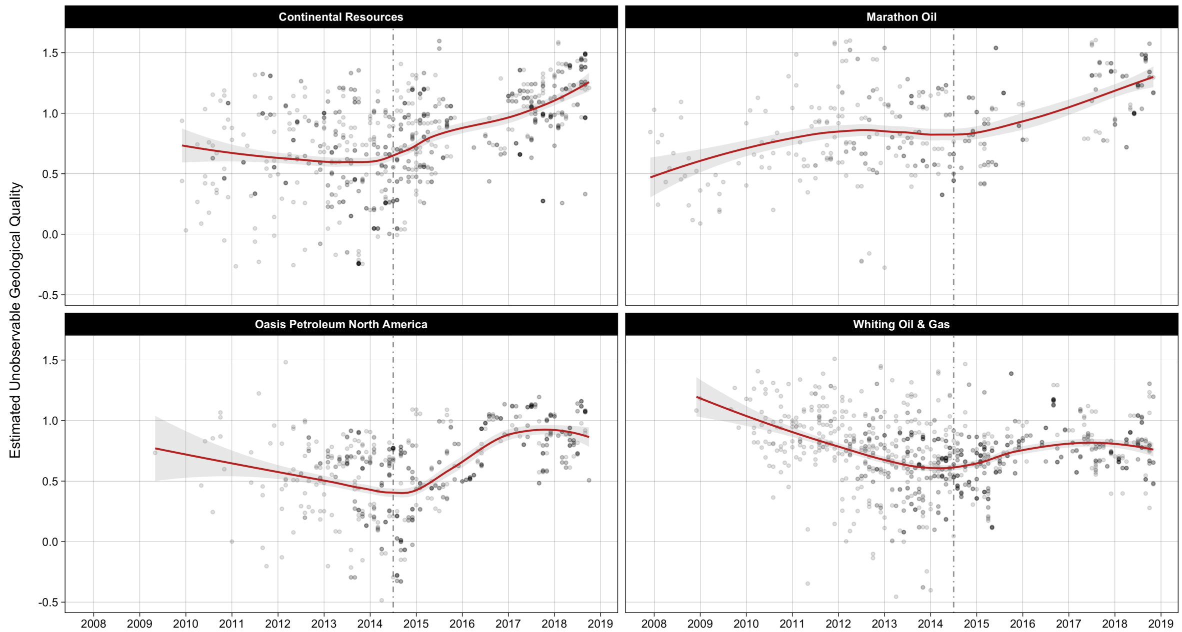

Figure 3.3: High Sensitivity of Firm-Level Low-Quality Well Drilling to the Negative Price Shocks in 2014-15

Note: This figure shows how the four firms' drilling activity changed over time. Each dot in the figure indicates an individual well's estimated geological feature. The red line, with the 95% confidence interval, in each panel demonstrates the average quality of horizontal wells drilled in a month. As illustrated, the firms significantly reduced drilling low-quality well locations since mid-2014, corresponding to the beginning of the oil price plunge.

Shocks — In addition to the simultaneous drilling of horizontal wells with heterogeneous qualities, Figure 3.2 demonstrates an interesting point: the responsiveness of low-quality well drilling to sharp oil price declines from mid-2014 to the end of 2015. The high sensitivity of drilling activities for low-quality horizontal wells to negative price shocks during the period is also pronounced even at the firm level, as illustrated in Figure 3.3.

Figure 3.4 shows that drilling associated with held-by-production did not drive the relationship between oil prices and low-quality well drilling, especially between mid-2014 and the end of 2015. The upper panel in the figure illustrates the by-quality time series of the number of horizontal wells drilled that are supposed to be drilling related to Held-By-Production (HBP). In our empirical analysis, we assume that for each of the sections into which horizontal wells in our sample were drilled, the purpose of the first drilling in that section was just HBP.[14]

[14] In the Public Land Survey System, a *section*, which is one of 36 sections in a township, is a one-mile-square area.

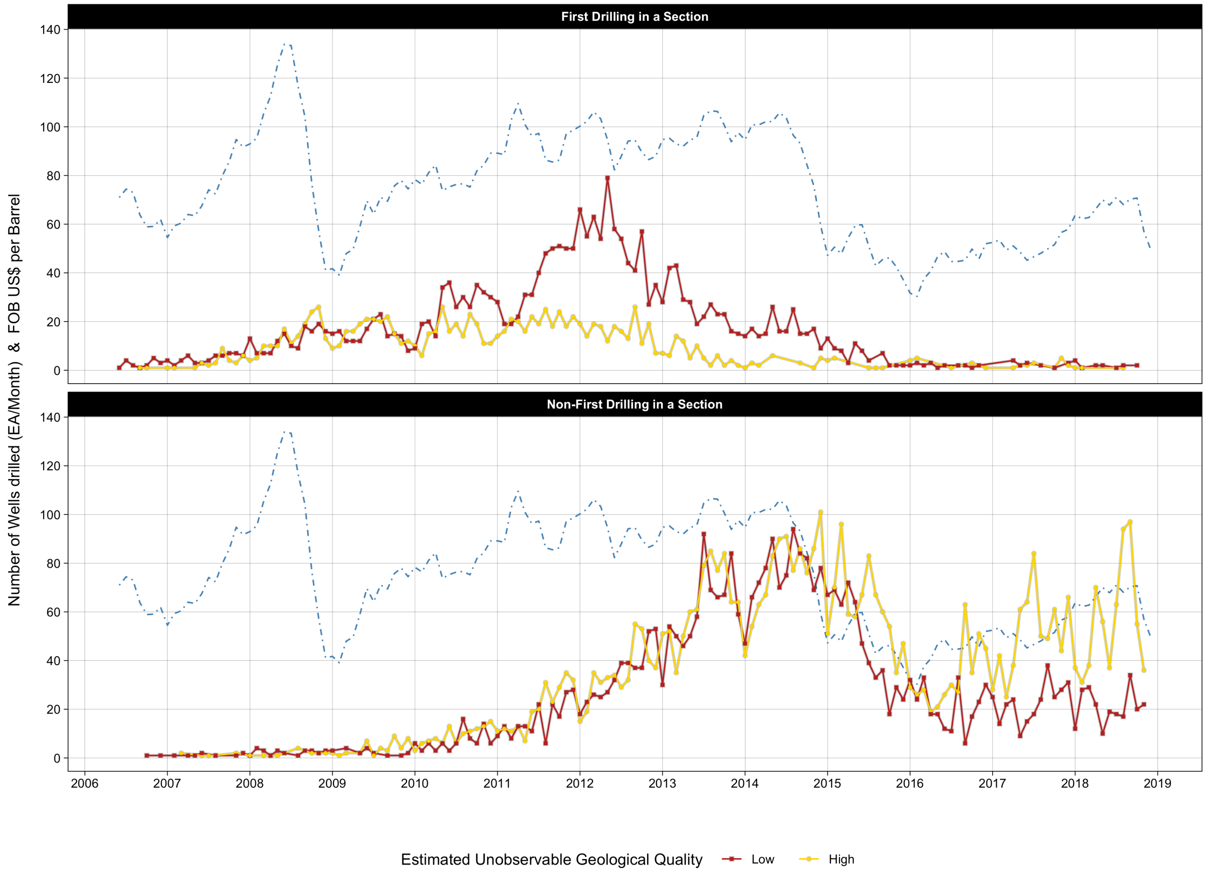

Figure 3.4: Held-by-Production vs. Non-Held-by-Production Horizontal Well Drilling

Note: This figure depicts the drilling of horizontal wells classified into two quality levels. The upper panel shows how the first drilling in each section, regarded as held-by-production drilling, has evolved. There was only a limited number of held-by-production drilling between 2015 and 2019. The lower panel indicates all subsequent drilling in sections. The collapse in oil prices between mid-2014 and 2015 made post-held-by-production drilling decrease. Drilling of low-quality well locations showed a more significant reduction, especially in 2015. High-quality sites were drilled more than low-quality ones during the period of oil price recovery from 2016 to 2019. In each panel, the dot-dashed line is the time series of the monthly per-barrel spot prices for West Texas Intermediate at Cushing, Oklahoma.

The relatively high drilling rate of low-quality wells, especially between mid-2011 and mid-2013, seems to be consistent with the empirical result of Herrnstadt, Kellogg and Lewis (2020): firms bound to a lease contract including use-it-or-lose-it requirements tend to drill low-productivity well locations just before the first lease expires.

The evolving pattern of drilling for each of the three quality levels presented in the lower panel of Figure 3.4, regarded as post-held-by-production drilling, shows completely different movements from those in the upper panel. Until 2014, horizontal wells of heterogeneous quality were drilled equally and at the same growth rate. But drilling of low-productivity horizontal wells more sensitively reacted to negative price shocks between mid-2014 and 2015, compared to drilling medium- and high-quality wells. The new theoretical approach, required to rationalize the simultaneous drilling of wells with heterogeneous qualities, needs to explain the high sensitivity of low-quality well drilling.

3.3 A DCDP Model in Continuous Time for Drilling Decisions in Oil and Gas Extraction

This section delves into the analysis of two distinct economic frameworks. In Section 3.3.1, the optimal drilling and extraction model developed in Anderson, Kellogg and Salant (2018) is reformulated by introducing heterogeneity in resource quality. And it is shown that the recast model cannot justify the empirically observed simultaneous drilling of well locations with varying quality levels. In the subsequent portions of this section, a continuous-time Discrete Choice Dynamic Programming (DCDP) model for oil and gas extraction is developed, successfully articulating the simultaneous drilling of horizontal wells with heterogeneous quality.

3.3.1 A Limitation of AKS-style Model

The theoretical framework for optimal oil drilling and extraction delineated in Anderson, Kellogg and Salant (2018) (AKS) can be augmented by integrating heterogeneity in the quality of well locations. Suppose that the fracking firm owns well sites of different qualities, indexed by $g \in \{L(ow), H(igh)\}$, and that a homogeneous good (i.e., oil) is yielded from the sites in which new horizontal wells are drilled. Furthermore, suppose that the unit price of the output, $\bar{p}$, is determined exogenously due to the firm's total production being negligible in comparison to the global market for the output. The maximization problem of the firm owning a continuum of infinitesimal well locations with disparate qualities can be articulated as follows:

$$\max_{d^g(t),\ g \in \{L,H\}} \int_0^\infty e^{-rt} \left\{ \bar{p} \sum_g \alpha^g d^g(t) \; - \; C\left(\sum_g d^g(t) \right) \right\} dt \tag{3.4}$$

subject to

$$\dot{R}^g(t) \; = \; -d^g(t), \quad R_0^g \; = \; R^g(0) \text{ given,} \tag{3.5}$$

$$d^g(t) \; \geqslant \; 0, \quad R^g(t) \; \geqslant \; 0. \tag{3.6}$$

In this formulation, state variables $R^g(t)$ denote the measure of undrilled well sites at a given time t. We simplify the AKS model by assuming that firms always produce at their production capacity constraint. This assumption reduces the complexity of the model. Control variables $d^g(t)$ represent the rate at which new horizontal wells are drilled at time t. α^g are the quantity of oil production from the marginally drilled well. Here, we assume that $\alpha^H > \alpha^L$. $C(\cdot)$, indicating the total instantaneous cost of drilling, is solely a function of the drilling rates.[15] Of note, in this formulation for $C(\cdot)$, we assume that locations are perfect substitutes on the cost side. And the profit obtained at time t is discounted at the interest rate r.

The current-value Hamiltonian-Lagrangian of the firm's problem is

$$\begin{aligned} \mathcal{H} \;=\; & \bar{p}\sum_g \alpha^g d^g(t) \;-\; C\left(\sum_g d^g(t)\right) \\ & +\; \sum_g \pi^g(t)\left(-d^g(t)\right) \\ & +\; \sum_g \lambda_1^g(t) d^g(t) \;+\; \sum_g \lambda_2^g(t) R^g(t), \end{aligned} \tag{3.7}$$

where π_R^g are costate variables for the state variables R^g. $\lambda_j,\ j \in \{1,2\}$ are the shadow cost of each constraint.

For a given quality level g, two necessary conditions characterize the firm's optimal rate of drilling:

$$d^g(t) \;\geqslant\; 0,\;\; \alpha^g\bar{p} \;-\; C'\left(\sum_g d^g(t)\right) \;-\; \pi^g(t) \;+\; \lambda_1^g(t) \;\leqslant\; 0,\;\; C.S., \tag{3.8}$$

$$\dot{\pi}^g(t) \;=\; r\pi^g(t) \;-\; \lambda_2^g(t). \tag{3.9}$$

When horizontal wells with heterogeneous quality are drilled simultaneously (i.e., for each g, $d^g(t) > 0$, which leads to $\lambda_1^g(t) = 0$), necessary condition (3.8) implies that the shadow price on the resource constraint at time t equals the profit on the marginal well:

$$\pi^g(t) \;=\; \alpha^g\bar{p} \;-\; C'\left(\sum_g d^g(t)\right). \tag{3.10}$$

In addition, when both types of horizontal well sites are not fully exhausted (i.e., for each g, $R^g(t) > 0$, which in turn $\lambda_2^g(t) = 0$), necessary condition (3.9) means that the shadow value of

[15] Regarding the total cost of oil production, we follow the assumption made in Anderson, Kellogg and Salant (2018): per-barrel extraction costs from existing wells are negligible.

the marginal undrilled well at time t grows at the rate of r:

$$\dot{\pi}^g(t) \;=\; r\pi^g(t). \tag{3.11}$$

The necessary conditions collectively suggest that the simultaneous drilling of horizontal wells with heterogeneous quality cannot be justified in the AKS framework when $d^g(t) > 0$ and $R^g(t) > 0$, which hold before all available well sites are developed. The following stems from equation (3.10):

$$\pi^H(t) \;-\; \pi^L(t) \;=\; (\alpha^H - \alpha^L)\bar{p}. \tag{3.12}$$

This relationship implies that the difference in the shadow value between high- and low-quality well locations is simply a revenue difference at any time t. And as shown below, differentiating equation (3.10) with respect to time implies that for a given $C''(\cdot)$, $\dot{d}^g(t)$ and $d^g(t)$ determine the value of the time derivative of $\pi^g_t(t),\ g \in \{L, H\}$ and that $\dot{\pi}^L_t(t)$ and $\dot{\pi}^H_t(t)$ have the same value at a given time t:

$$\dot{\pi}^L(t),\ \dot{\pi}^H(t) \;=\; -\left(\sum_g \dot{d}^g(t)\right) C''\left(\sum_g d^g(t)\right). \tag{3.13}$$

Here, based on equation (3.11), the relationship between the time derivatives for two distinct qualities indicates that $\pi^L(t) = \pi^H(t)$ holds at all time t. However, this equality contradicts equation (3.12) because $\alpha^H > \alpha^L$. In other words, the simultaneous drilling of horizontal wells with heterogeneous quality does not hold in the AKS framework.

Adding a constraint on extraction capacity, as is done in Holland (2003), can suggest that simultaneous extraction of different resource qualities is optimal. However, in the framework, setting the upper bound of an extraction-related constraint seems too arbitrary and complicates drawing implications from necessary conditions. From the empirical perspective, it is also intractable to quantify the margin for market-wide, or firm-wide, extraction capacity for each drilling decision. Furthermore, empirical estimation of the model from microeconomic data on drilling and production is, in general, too demanding. Those difficulties call for a new theoretical approach that thoroughly explains our empirical findings for drilling decisions made by fracking firms in North Dakota.

The need leads us to develop a continuous-time Discrete Choice Dynamic Programming (DCDP) model that formulates a firm's drilling decision on a particular well site as an optimal stopping problem. Under this new theoretical framework, we can rationalize the simultaneous drilling of horizontal wells with heterogeneous resource quality without specifying any capacity constraint. Moreover, our DCDP model yields empirically testable predictions about how firms' drilling and production activities vary with oil prices. In the next section, we will present the basic elements and assumptions of our DCDP framework.

3.3.2 Setup

In our DCDP framework, in which time is continuous and indexed by $t \in [0, \infty)$, we assume a continuum of infinitesimally small potential drilling sites in which horizontal wells will be developed. Let R_t denote the measure of undrilled well sites at time t. In the AKS framework, R_t is the remaining reserves at time t. Therefore, the two can be equal but do not have to be. Without loss of generality, we fix the initial level of potential well sites in the market to be the value of one (i.e., $R_0 = 1$). For simplicity, it is also assumed that only one horizontal well is drilled into an infinitesimal site.

Each infinitesimal well site is owned by a single fracking firm indexed by an integer scalar $i = 1, 2, \cdots$.[16] A Poisson arrival process with rate parameter λ_a governs firms' drilling opportunity. In other words, for the firm i, an opportunity to drill arrives at rate λ_a. When a drilling opportunity arrives at time t, the firm i makes a choice at time t, denoted a_{it}, between two alternatives in a discrete choice set $\mathcal{A} = \{0, 1\}$:

$$a_{it} = \begin{cases} 0 & \text{if the firm decides not to drill a well in the site} \\ 1 & \text{if the firm decides to drill a well in the site.} \end{cases} \tag{3.14}$$

As implied, a_{it} is a well-site-level control variable. If the choice made by the firm i at time t is $a_{it} = 0$, the firm has another drilling opportunity that comes later. In other words, $a_{it} = 0$ is a costless continuation choice. On the other hand, when $a_{it} = 1$, the firm i exits the market after drilling a horizontal well into the site and producing oil from it.

The oil production from the horizontal well drilled into site i at time t is assumed to occur only during the same period:

$$q_t = \alpha a_{it}, \tag{3.15}$$

where α is the amount of oil produced from a well. For simplicity, we assume that α is a constant across locations. This formulation can certainly be modified to allow for production decline over

[16] In this paper, we use i to denote a potential well site or a firm interchangeably.

time. However, we mainly focus on firms' investment and drilling decisions, so we abstract away from production declines. In an empirical exercise, account for the fact that a well produces for multiple periods by assuming that firms sell their production forward and receive the present value of revenue at the time they drill and complete the well.

The linear cost of drilling a horizontal well into the site i is assumed. That is,

$$c_t \;=\; ca_{it}. \tag{3.16}$$

For simplicity, it is also assumed that the drilling cost for the marginal well is uniform across well sites (i.e., c is the same for all potential well locations.). In addition, as in Section 3.3.1, we take the assumption of the negligible extraction costs.

In our theoretical framework, firms' site-level drilling decisions can be easily aggregated at the market level. It is natural to define aggregate drilling in the market at time t, denoted D_t, as follows:

$$D_t \;\equiv\; \int_{\lambda_a R_t} a_{it}\; di. \tag{3.17}$$

In this definition, $\lambda_a R_t$ indicates a group of potential sites into which a horizontal well can be drilled when a drilling opportunity arrives at time t.[17] If each potential well site has the same probability of drilling a horizontal well into it at time t (denoted Pr_t), then D_t can be expressed as follows[18]:

$$D_t \;=\; \lambda_a R_t Pr_t. \tag{3.18}$$

We further assume that each period, measure E locations are also exogenously discovered and added to the set of potential sites. We ignore the exploration-associated costs in our formulation. So, the evolution path of the remaining well sites is governed by the following relationship:

$$\dot{R}_t \;\equiv\; -D_t \;+\; E \;=\; -\lambda_a R_t Pr_t \;+\; E. \tag{3.19}$$

In addition, because we assume that α is uniform across potential sites, aggregate oil production in the market at time t, denoted Q_t, is simply proportional to D_t:

$$Q_t \;\equiv\; \alpha D_t \;=\; \alpha\lambda_a R_t Pr_t. \tag{3.20}$$

[17]This interpretation implies $\lambda_a \leqslant 1$.

[18]In the expression, $\lambda_a Pr_t$ indicates the probability of drilling a potential well site in the next instant, given it has not been drilled to time t. That is, $\lambda_a Pr_t$ is the hazard rate at time t, denoted h_t. Therefore, it is natural that $D_t = R_t h_t$.

Oil prices are discretized. For a given oil production Q, the following inverse demand function determines the oil price[19]:

$$p_k \;=\; p_{0,k} \;-\; \bar{p}_1 Q. \tag{3.21}$$

Here, k is an integer scalar index $k = 1, 2, \cdots, K$, by which every available demand level $p_{0,k}$ in a finite state space $\mathcal{X}$ is enumerated.[20] Moreover, $p_{0,k}$ and $\bar{p}_1$ are non-negative. Oil prices determined by the function can vary due to a finite-state Markov jump process.[21] The process is a jump process on $\mathcal{X}$. Parameters $\lambda_{k\ell}$ that indicate the rates at which particular exogenous state transitions from k to $\ell \neq k$ occur govern this process. This formulation allows oil prices to evolve endogenously in a smooth way, and it also accommodates stochastic price jumps. It is also assumed that all firms in the market take oil prices as given in a competitive equilibrium.

An infinitesimal well site provides two different types of payoffs. First, each undrilled well site generates a continuous and constant flow payoff (denoted f_t) that could be zero or negative. Second, choosing an action in the choice set $\mathcal{A}$ when a drilling opportunity arrives at time t yields an instantaneous payoff. An additively separable payoff function, denoted $U(\boldsymbol{X}_t, \epsilon_t)$, represents the instantaneous payoff:

$$U(\boldsymbol{X}_t, \epsilon_t) \;=\; \begin{cases} 0 \;+\; \epsilon_{0t} & \text{if } \; a_t = 0 \\ \psi(\boldsymbol{X}_t) \;+\; \epsilon_{1t} & \text{if } \; a_t = 1. \end{cases} \tag{3.22}$$

In the payoff function, $\boldsymbol{X}_t$ is a vector of relevant state and control variables. In addition, $\psi(\cdot)$ and ϵ_{at} indicate a choice-specific instantaneous payoff from oils produced from the site and choice-specific cost shocks, respectively. Of note, contrary to the flow payoff, the instantaneous payoff is applicable only to potential well locations under a drilling opportunity.

The choice-dependent instantaneous payoff $\psi(\cdot)$ is defined differently for two maximization problems, the social planner's and firm's problems, which will be discussed in the following sections. Specifically, in the social planner's problem, the instantaneous payoff is the net benefit achieved by consuming oils produced from drilled well sites in the market:

$$\begin{aligned} \psi(Q_t, D_t) \;&=\; u(Q_t) \;-\; c(D_t) \\ &=\; u(\alpha R_t Pr_t) \;-\; c(R_t Pr_t). \end{aligned} \tag{3.23}$$

[19] For simplicity, we omit the t subscript in the inverse demand function.

[20] In other words, $\mathcal{X}$ is a discrete state space for $p_{0,k}$.

[21] A Markov jump process with finite states is a stochastic process that has discrete movements governed by a Poisson arrival process. For details, see Doytchinov and Irby (2010).

Here, $u(\cdot)$ is the total utility obtained from oil consumption at time t, whereas $c(\cdot)$ is the total drilling cost at time t. For the case of $Q_t = 0$, $u(\cdot)$ and $c(\cdot)$ are normalized to zero.[22] Of note, $\boldsymbol{X}_t = (Q_t, D_t)$ in this maximization problem.[23] On the other hand, in the firm's problem, the instantaneous payoff is simply the net profit from oil production. So, if the firm i's choice is $a_{it} = 1$ when a drilling opportunity arrives at time t, then

$$\psi(p_k) \;=\; \alpha p_k \;-\; c. \tag{3.24}$$

Here, the firm i is supposed to be in state k. As shown, $\boldsymbol{X}_t = (p_k)$ in the firm's problem.

In the payoff function, ϵ_{at}, a component of the payoff of an alternative a, is an idiosyncratic cost shock at time t.[24] In our context, ϵ_{at}, which relies on the choice of a decision maker (e.g., the social planner or the firm), can be perceived as a composite cost element that affects the decision maker's choice at time t between drilling today and drilling in the future and that varies over time. For example, for the firm i, ϵ_{at} could include capacity-constraint-induced costs, whose value varies with a_{it}. With the interpretation of ϵ_{at}, it is not required to specifically model a set of constraints at time t in our framework.

The choice-specific cost shock ϵ_{at} drives the decision maker's drilling decision at time t. Because the shock is observable only by it, without ϵ_{at}, the (observable) state variable cannot perfectly explain the choice at time t in our model. Intuitively, when the decision maker decides whether to drill a well into a given well site or not at time t, $a_t = 1$ will be the optimal choice if the value of the payoff function conditional on $a_t = 1$ is greater than or equal to that conditional on $a_t = 0$. Mathematically,

$$\begin{aligned} \psi(\boldsymbol{X}_t) \;+\; \epsilon_{1t} \;&\geqslant\; \epsilon_{0t} \\ \epsilon_{1t} \;-\; \epsilon_{0t} \;&\geqslant\; -\psi(\boldsymbol{X}_t). \end{aligned} \tag{3.25}$$

The decision rule implies that the magnitude of $\epsilon_{1t} - \epsilon_{0t}$ determines the optimal choice.

Since ϵ_{at} is not observable, utilizing the decision rule directly is infeasible. However, according to Aguirregabiria and Magesan (2013), the expected value of ϵ_{at} conditional on alternative a_t

[22]From equation (3.20), it is clear that $Q_t = 0$ implies $D_t = 0$.

[23]In the social planner's problem, the state and control variables are R_t and Pr_t, respectively. For details, see Section 3.3.3.

[24]We can regard $\epsilon_{a,t}$ as an element of the unobservable state vector $\boldsymbol{\epsilon}_t$. In our case that $\mathcal{A} = \{0, 1\}$, $\boldsymbol{\epsilon}_t = (\epsilon_{0t},\ \epsilon_{1t})$.

being chosen under the decision rule can be expressed with Pr_t. To be specific, when $a_t = 1$, the conditional expected value of ϵ_{1t}, denoted e_{1t}, is given as follows[25]:

$$e_{1t} \;\equiv\; E[\epsilon_{1t} \mid a_t = 1] \;=\; \sigma\left(\gamma \;-\; \ln(Pr_t)\right). \tag{3.26}$$

Here, γ is Euler's constant. And it is assumed that ϵ_{at} follow the Type 1 Extreme Value (T1EV) distribution with the location parameter 0 and the scale parameter σ and are independently and identically distributed. The expected value allows our analytical as well as empirical analysis of drilling decisions to be tractable without observing ϵ_{at}. Throughout this paper, we keep the assumption about the distribution of the cost shocks.

3.3.3 Social Planner's Problem and Necessary Conditions

In this section, using the continuous-time DCDP framework, we develop the social planner's problem. When an opportunity to drill potential well sites arrives, the social planner makes two decisions. First, the planner must choose, via the choice of Pr_t, the aggregate quantity of drilling. Second, the planner must also decide which locations will be drilled. Each site can be indexed by $\epsilon_{1t} - \epsilon_{0t}$, and so selecting which sites to drill can be thought of as selecting which indices to drill. Because there is a continuum of potential well locations, determining the optimal policy (i.e., the optimal Pr_t) is simply to choose a threshold that does not depend on the specific set of cost shocks realized at time t. Potential well locations with indices above the threshold drill, whereas those below it wait to drill. The one-to-one mapping between the threshold index and the choice of Pr_t is characterized by equation (3.25).

The goal of the social planner is to maximize welfare in the market. In this maximization problem, for a given Pr_t, the market's welfare obtained from potential well sites at time t is defined as follows[26]:

$$\begin{aligned} W_t^{sp} \;\equiv\;& R_t f_t \\ &+\; u(\alpha\lambda_a R_t Pr_t) \;-\; c(\lambda_a R_t Pr_t) \\ &+\; \lambda_a R_t \Big\{ Pr_t \cdot \sigma\big(\gamma \;-\; \ln(Pr_t)\big) \;+\; (1 - Pr_t)\cdot\sigma\big(\gamma \;-\; \ln(1 - Pr_t)\big) \Big\} \end{aligned} \tag{3.27}$$

As shown, the welfare of the market at time t consists of three components.[27] The first line indicates the flow payoff received from undrilled well locations at time t. The second line means

[25] In other words, e_{at} indicate the mean of the cost shock conditional on choice a_t.

[26] Using D_t, we can re-write the definition: $W_t^{sp} \;=\; R_t f_t \;+\; u(\alpha D_t) \;-\; c(D_t) \;+\; D_t\sigma\big(\gamma \;-\; \ln(Pr_t)\big) \;+\; (\lambda_a R_t - D_t)\sigma\big(\gamma \;-\; \ln(1 - Pr_t)\big)$.

[27] W_t^{sp} can be interpreted differently. To be specific, W_t^{sp} is the sum of the flow payoff from the undrilled

the choice-specific instantaneous payoff, which is presented as equation (3.23). The last line suggests the payoff related to choice-specific cost shocks.[28] Note that regarding the choice-dependent cost shocks, their expected value is used and that only the terms in the last two lines, which depend on the social planner's drilling decisions, are associated with λ_a.

In the continuous-time DCDP framework, the social planner's welfare problem is given by

$$W^{sp*} = \max_{\{Pr_t\}_{t=0}^{\infty}} \int_0^{\infty} e^{-rt} W_t^{sp} \, dt \tag{3.28}$$

subject to

$$\dot{R}_t = -\lambda_a R_t Pr_t + E, \quad R_0 = R(0) = 1 \text{ given,} \tag{3.29}$$

$$R_t \geqslant 0, \quad 0 < Pr_t < 1. \tag{3.30}$$

As shown, W_t^{sp} is discounted at the rate of interest r.

Under the assumption of an interior solution, the current-value Hamiltonian-Lagrangian of the social planner's problem is given by

$$\begin{aligned} \mathcal{H}^{sp} = \; & R_t f_t \\ & + u(\alpha \lambda_a R_t Pr_t) - c(\lambda_a R_t Pr_t) \\ & + \lambda_a R_t \big\{ Pr_t \cdot \sigma\big(\gamma - \ln(Pr_t)\big) + (1 - Pr_t) \cdot \sigma\big(\gamma - \ln(1 - Pr_t)\big) \big\} \\ & + \pi_t(-\lambda_a R_t Pr_t + E). \end{aligned} \tag{3.31}$$

The necessary conditions of the current-value Hamiltonian-Lagrangian are as follows:

$$\lambda_a R_t \big\{ \alpha u'(\alpha \lambda_a R_t Pr_t) - c'(\lambda_a R_t Pr_t) - \sigma \ln(Pr_t) + \sigma \ln(1 - Pr_t) - \pi_t \big\} \leqslant 0, \tag{3.32}$$

$$\dot{\pi}_t = r\pi_t - \big\{ f_t + \lambda_a \sigma\big(\gamma - \ln(1 - Pr_t)\big) \big\}, \tag{3.33}$$

$$\lim_{t \to \infty} e^{-rt}(R_t \pi_t) = 0. \tag{3.34}$$

---

well sites at time t (i.e., $R_t f_t$), the net (expected) payoff obtained from the marginally drilled well site at time t $\big($i.e., $u(\alpha\lambda_a R_t Pr_t) - c(\lambda_a R_t Pr_t) + \lambda_a R_t Pr_t \sigma\big(\gamma - \ln(Pr_t)\big)\big)$, and the (expected) gains from the well sites that are available but decided not to drill at time t $\big($i.e., $\lambda_a R_t (1 - Pr_t)\sigma\big(\gamma - \ln(1 - Pr_t)\big)\big)$.

[28]The last line in equation (3.27) can be rewritten using e_0 and e_1:

$$\lambda_a R_t \big\{ Pr_t \cdot \sigma\big(\gamma - \ln(Pr_t)\big) + (1 - Pr_t) \cdot \sigma\big(\gamma - \ln(1 - Pr_t)\big) \big\} = \lambda_a R_t \big\{ Pr_t \cdot e_1 + (1 - Pr_t) \cdot e_0 \big\}.$$

If $R_t > 0$, necessary condition (3.32) yields the following expression for the costate variable π_t, which is a function of R_t and Pr_t:

$$\begin{aligned} \pi_t &= \alpha u'(\alpha\lambda_a R_t Pr_t) \;-\; c'(\lambda_a R_t Pr_t) \;-\; \sigma \ln(Pr_t) \;+\; \sigma \ln(1 - Pr_t) \\ &= \big\{\alpha u'(\alpha\lambda_a R_t Pr_t) \;-\; c'(\lambda_a R_t Pr_t) \;+\; \sigma\big(\gamma \;-\; \ln(Pr_t)\big)\big\} \;-\; \sigma\big(\gamma \;-\; \ln(1 - Pr_t)\big). \end{aligned} \tag{3.35}$$

In addition, substituting condition (3.35) into condition (3.33) yields the following Euler equation that governs the dynamics of the social planner's welfare maximization problem over time:

$$\begin{aligned} &\frac{\dot{\pi}_t \;+\; \big\{f_t \;+\; \lambda_a\sigma\big(\gamma \;-\; \ln(1 - Pr_t)\big)\big\}}{r} \\ &= \alpha u'(\alpha\lambda_a R_t Pr_t) \;-\; c'(\lambda_a R_t Pr_t) \;+\; \sigma\big(\gamma \;-\; \ln(Pr_t)\big) \;-\; \sigma\big(\gamma \;-\; \ln(1 - Pr_t)\big). \end{aligned} \tag{3.36}$$

We will discuss the implications of necessary conditions (3.33) and (3.35) later.

The social planner's problem has a unique steady state (R_{ss}, π_{ss}) such that $\dot{R}_{ss},\ \dot{\pi}_{ss} = 0$. From necessary conditions (3.29) and (3.33), R_t and π_t must satisfy the following equations at steady state:

$$\begin{cases} R_{ss} &= \dfrac{E}{\lambda_a Pr_{ss}} \\ \pi_{ss} &= \dfrac{f_t \;+\; \lambda_a\sigma\left(\gamma \;-\; \ln(1 - Pr_{ss})\right)}{r}. \end{cases} \tag{3.37}$$

On top of the equations, necessary condition (3.35) has to hold at the steady state simultaneously. Solving the system of three equations, we can uniquely identify (R_{ss}, π_{ss}), including the value of the control variable at the steady state (i.e., Pr_{ss}). As implied by the first equation in (3.37), R_{ss} is non-zero positive if $E \neq 0$. Using a Taylor series approximation, $\dot{R}_t$ and $\dot{\pi}_t$ can be linearized near the steady state (R_{ss}, π_{ss}), and this linearization process shows that the steady state of the infinite-horizon maximization problem is a saddle point, which is demonstrated in Figure 3.5.[29]

3.3.3.1 Implications of Necessary Conditions

Necessary conditions (3.33) and (3.35) have important economic implications of the optimal path of well sites' depletion. Firstly, necessary condition (3.33) demonstrates significant implications

[29] Regarding the saddle property, see *9.5 Steady states in autonomous infinite-horizon problems* in Leonard and Long (1992). And derivation details are provided in A.3.1.1.

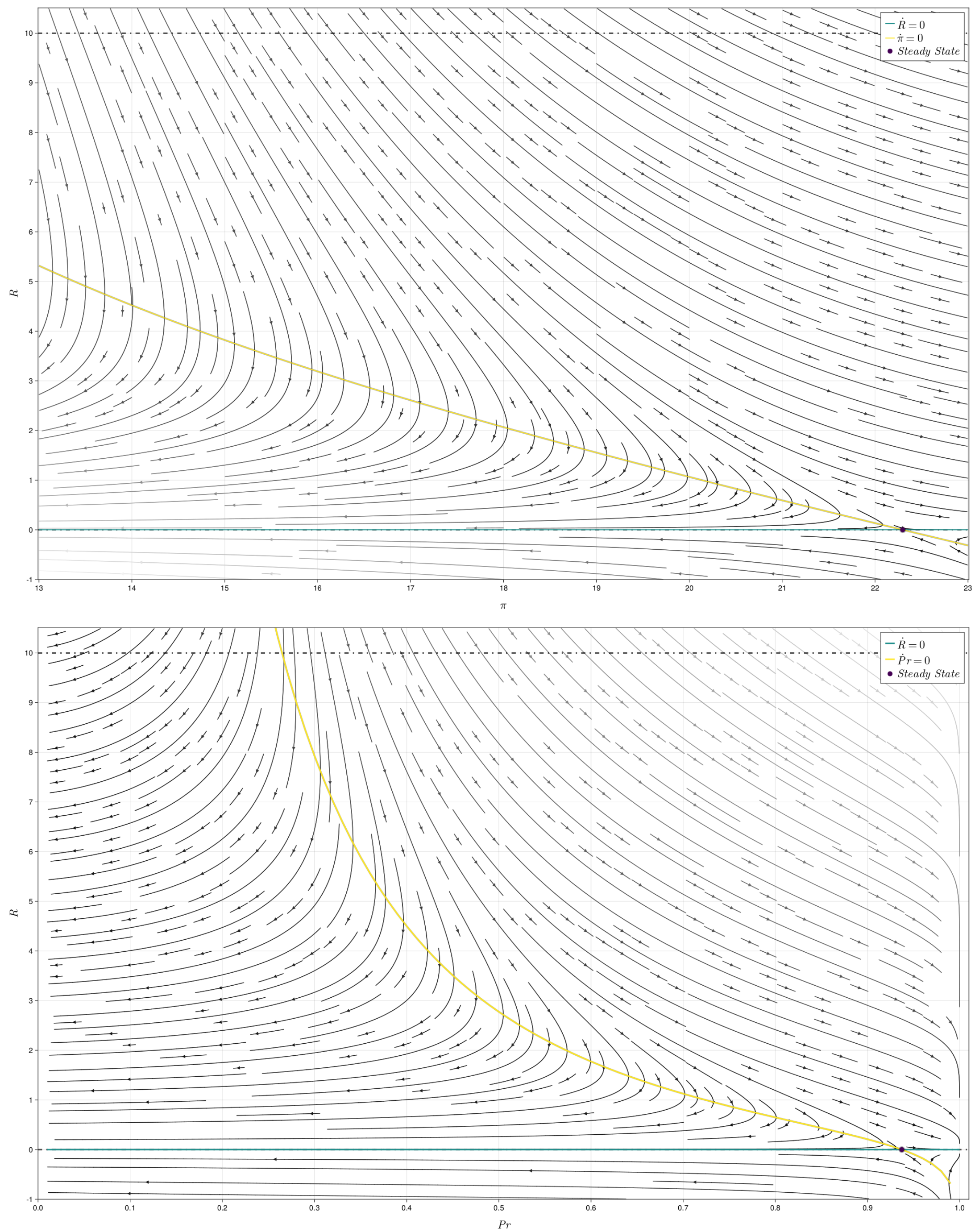

Figure 3.5: Phase Diagrams for the Social Planner's Problem

Note: This figure demonstrates two phase diagrams for the social planner's problem. The upper diagram illustrates that the steady state is exactly a saddle point. This figure assumes that a dispersion parameter of $\sigma = 1$, an interest rate of $r = 0.15$, an initial number of well sites of $R_0 = 10$, additional well sites of $E = 0$, and exogenously given constant oil prices of $p = 50$. Also, a linear cost function of $c(D_t) = 2D_t$ is assumed.

of π_t's growth over time. We can re-express this condition as follows[30]:

$$\dot{\pi}_t \;=\; r\left\{\pi_t \;-\; \frac{f_t \;+\; \lambda_a\sigma\big(\gamma \;-\; \ln(1-Pr_t)\big)}{r}\right\}. \tag{3.38}$$

This expression clearly indicates that π_t grows slower than the rate of interest r. The necessary condition also suggests that π_t increases concavely with Pr_t and converges in the limit, unlike the exponential growth of the shadow price in Hotelling's framework.[31]

Secondly, necessary condition (3.35) directly provides us with what π_t means. In this condition, the three terms in the curly bracket collectively mean the net benefit from the output (i.e., oils) produced from the marginally drilled well site at time t. The last term among them is the expected value of the cost shock for the marginal well location at time t when the social planner decides to drill it (i.e., e_{1t}). The remaining term in this condition represents the opportunity cost of drilling the marginal site at time t.[32] Hence, the necessary condition indicates that the costate variable π_t implies the net shadow value of the marginally drilled well site in the current-value term at time t.

Necessary condition (3.33) also enables us to understand what π_t means from a different perspective. We can re-write this necessary condition as follows:

$$\pi_t \;=\; e^{rt}\left[\lim_{T\to\infty}\int_t^T e^{-r\tau}\Big\{f_t \;+\; \lambda_a\sigma\big(\gamma \;-\; \ln(1-Pr_\tau)\big)\Big\}\, d\tau\right]. \tag{3.39}$$

This equation implies that π_t is the marginally undrilled well site's aggregate future payoff (i.e., the sum of the flow payoff and the expected value of ϵ_{0t}'s from time t and beyond), as the current value at time t, if the well site will remain undeveloped. Therefore, it is clear that drilling well locations is economic depletion in our framework, as extracting an exhaustible resource is in Hotelling's model.

[30] Because $\dot{\pi}_t$ must be zero at the steady state, this equation implies that $\pi_t = \big\{f_t \;+\; \sigma\big(\gamma \;-\; \ln(1-Pr_t)\big)\big\}/r$ at the steady state. It is clear that both f_t and Pr_t must be a constant at the steady state. Based on this observation, we can draw the same expression for π_t at the steady state from equation (3.39): $\pi_t = e^{rt}\big\{f_t \;+\; \sigma\big(\gamma \;-\; \ln(1-Pr_t)\big)\big\}\int_t^\infty e^{-r\tau}\, d\tau = \big\{f_t \;+\; \sigma\big(\gamma \;-\; \ln(1-Pr_t)\big)\big\}/r$.

[31] From the beginning of drilling (i.e., $t = 0$), R_t decreases. If Pr_t is maintained at the initial level, the rate of drilling will quickly converge to zero. So, Pr_t must continuously grow to keep drilling. In equation (3.38), the increase in Pr_t leads to the reduction in $\dot{\pi}_t$. Moreover, as discussed earlier, Pr_t approaches to Pr_{ss}.

[32] If the social planner decides not to drill a horizontal well into the marginal well site at time t, then the expected value of ϵ_{0t} conditional on $a_t = 0$ (i.e., e_{0t}) is the only gain the social planner gets from the decision.

From the above discussions, necessary conditions (3.35) and (3.39) collectively suggest that on the optimal path of drilling, the marginal undeveloped well site will be drilled at time t if the net gains from drilling it at time t equal the undrilled site' aggregate future gains from time t and beyond. In other words, at the margin, drilling a horizontal well today is an optimal choice if its value is indifferent to the value of simply holding it forever. Indeed, this implication holds under the Hotelling framework.

In addition, the costate variable π_t can be expressed in terms of W_t^{sp}. Specifically, π_t, which indicates the net shadow value of the marginally drilled well site as the current value at time t, is the marginal welfare with respect to D_t as shown below:

$$\frac{\partial W_t^{sp}}{\partial D_t} = \alpha u'(\alpha D_t) - c'(D_t) + \sigma\big(\gamma - \ln(Pr_t)\big) - \sigma\big(\gamma - \ln(1 - Pr_t)\big). \tag{3.40}$$

That is, the marginally drilled site's shadow value is the same as the marginal welfare of drilling.

The value of σ, which is the dispersion parameter of the I.I.D. T1EV cost shocks, provides two interesting implications. First, the social planner's problem reverts to the Hotelling model of the optimal extraction of a nonrenewable resource when σ goes to zero. Taking limits to zero for necessary conditions (3.33) and (3.35) with the assumption of $f_t = 0$ yields the followings, which are identical to the two necessary conditions in Hotelling's classic model of depletion[33]:

$$\begin{cases} \lim\limits_{\sigma \to 0} \dot{\pi}_t = r\pi_t \\ \lim\limits_{\sigma \to 0} \pi_t = \alpha u'(\alpha \lambda_a R_t Pr_t) - c'(\lambda_a R_t Pr_t). \end{cases} \tag{3.41}$$

Intuitively, the limiting case that σ takes the value of zero means that the drilling decision for the marginal well location depends only on drilling costs and the interest rate r, which are not stochastic, unlike cost shocks ϵ_{at}'s.

Second, the magnitude of σ determines the rate of drilling, and also production. To be specific, an increase in the magnitude of σ reduces the drilling rate. When the value of σ grows, the importance of the cost shocks increases relative to the observable components in the payoff function (i.e., $\psi(\boldsymbol{X}_t)$). In other words, as more payoff comes from the cost shocks, the option value of each well location increases. Therefore, a larger value of σ makes the social planner wait for a better cost shock, which in turn, delays well drilling.

[33]We take the assumption of zero flow payoff because the payoff element is not introduced in Hotelling's theoretical model.

Transversality condition (3.34) rules out too aggressive depletion of well sites. Note that the transversality condition holds even when $R_t \neq 0$.

3.3.4 Firm's Problem

In this section, we develop the firm's problem under the settings of our DCDP model in continuous time. We first introduce additionally required building blocks. In particular, we integrate heterogeneity in the quality of well sites into the problem. Following Arcidiacono et al. (2016), we formulate the value function for a given well site. And then, utilizing the value function, we show that the oil market clears. In addition, we formulate firm-level optimal paths by aggregating the firm's well-level drilling decisions.

3.3.4.1 Firm's Decisions on Drilling Well Sites

In this section, we develop the firm's problem under the settings of our DCDP model in continuous time. Following Arcidiacono et al. (2016), we formulate the value function for a particular potential well site owned by the firm i that is forward-looking and discounts future payoffs at rate $\rho \in (0, \infty)$. Specifically, when the site is in state k, its value function is given as follows[34]:

$$-\dot{V}_{ik} + \left(\rho + \lambda_a + \sum_{\ell \neq k} \lambda_{k\ell}\right) V_{ik} = f_{ik} + \lambda_a E\Big[\max_{a \in \mathcal{A}} \{V_{ik} + \psi_{iak} + \epsilon_{iak}\}\Big] + \sum_{\ell \neq k} \lambda_{k\ell} V_{i\ell}. \tag{3.42}$$

For the site, the value function V_{ik} represents the present discounted value of all payoffs obtained from starting at state k and behaving optimally in all subsequent periods.[35] Here, it is assumed that the firm i's drilling decisions have no impact on the price of oil in the market.[36] $\dot{V}_{ik}$ is the time derivative of V_{ik}. The three terms in the round bracket on the left-hand side are the sum of the discount factor and the rates at which the state can change. The right-hand side consists of the flow payoff, the expected value relying on the firm's decisions, and the rate-weighted value related to exogenous state transitions. The expectation is for the joint distribution of ϵ_{i0k} and ϵ_{i1k}. While adding in the T1EV cost shocks is tedious, it also allows us to reconcile an empirical, firm-level model with aggregate time paths of resource extraction.

For a given opportunity to choose an action $a \in \mathcal{A}$, the probability of drilling a horizontal

[34] Detailed derivation is presented in A.3.1.2.

[35] Although V_{ik} varies over time, we omit the t subscript for simplicity.

[36] In other words, the assumption implies that the resulting state of taking action a by the firm i, denoted $\ell(i, a, k)$, is k.

well into the potential site conditional on state k, denoted Pr_k, can be defined as follows[37]:

$$Pr_k \equiv \Pr\left[\ \psi_{i1k} + \epsilon_{i1k} \geqslant V_{ik} + \psi_{i0k} + \epsilon_{i0k} \mid k\ \right]. \tag{3.43}$$

As shown in Arcidiacono et al. (2016), for each action $a \in \mathcal{A}$, the second term on the right-hand side of equation (3.42) is

$$\lambda_a E\Big[\max_{a \in \mathcal{A}} \{V_{ik} + \psi_{iak} + \epsilon_{iak}\}\Big] = \underbrace{\lambda_a \left\{V_{ik} + \sigma\big(\gamma - \ln(1 - Pr_k)\big)\right\}}_{\text{if } a=0} = \underbrace{\lambda_a \left\{\psi_{i1k} + \sigma\big(\gamma - \ln(Pr_k)\big)\right\}}_{\text{if } a=1}, \tag{3.44}$$

where the choice-specific instantaneous payoff function for $a = 1$ (i.e., ψ_{i1k}) is the function (3.24).

Under the assumption that there is no exogenous demand shock, some algebraic manipulation on the value function (3.42), with the expressions in (3.44), yields the Euler equation that drives the dynamics of the firm's optimal drilling decisions[38]:

$$\begin{aligned} &\frac{\dot{V}_{ik} + f_{ik} + \lambda_a \sigma\big(\gamma - \ln(1 - Pr_k)\big)}{\rho} \\ &= \alpha p_k - c + \sigma\big(\gamma - \ln(Pr_k)\big) - \sigma\big(\gamma - \ln(1 - Pr_k)\big). \end{aligned} \tag{3.45}$$

The left-hand side of this equation represents the sum of the instantaneous change in V_{ik} and the firm's expected payoff when deciding not to drill a horizontal well into the site as the current value at the time point of decision. In the equation, the right-hand side, which is equal to V_{ik} as shown in A.3.1.3, is the firm's payoff if it chooses to drill a horizontal well into the site, including the opportunity cost of the decision. In other words, V_{ik} is the well location's net shadow value as the current value, which is represented as π_t in the necessary conditions for the social planner's problem. Based on the relationship between V_{ik} and π_t, it is evident that the Euler equation (3.45) drawn from the firm i's well-site-level decisions coincides with the Euler equation (3.36) of the social planner's welfare maximization problem.[39]

[37] For given values of parameters, we can compute the value of each Pr_k, $k = 1, 2, \cdots, K$, by using value function iterations.

[38] See A.3.1.3 for details.

[39] There are two differences between the Euler equations. First, the rate of interest r is used in the social planner's problem, whereas the discount rate ρ is utilized in the firm's problem. Second, we exploit two different choice-specific instantaneous payoff functions, which are demonstrated in (3.23) and (3.24), in the two dynamic optimization problems. Of note, both of the choice-specific instantaneous payoff functions indicate the net benefit obtained from the output of drilling activities.

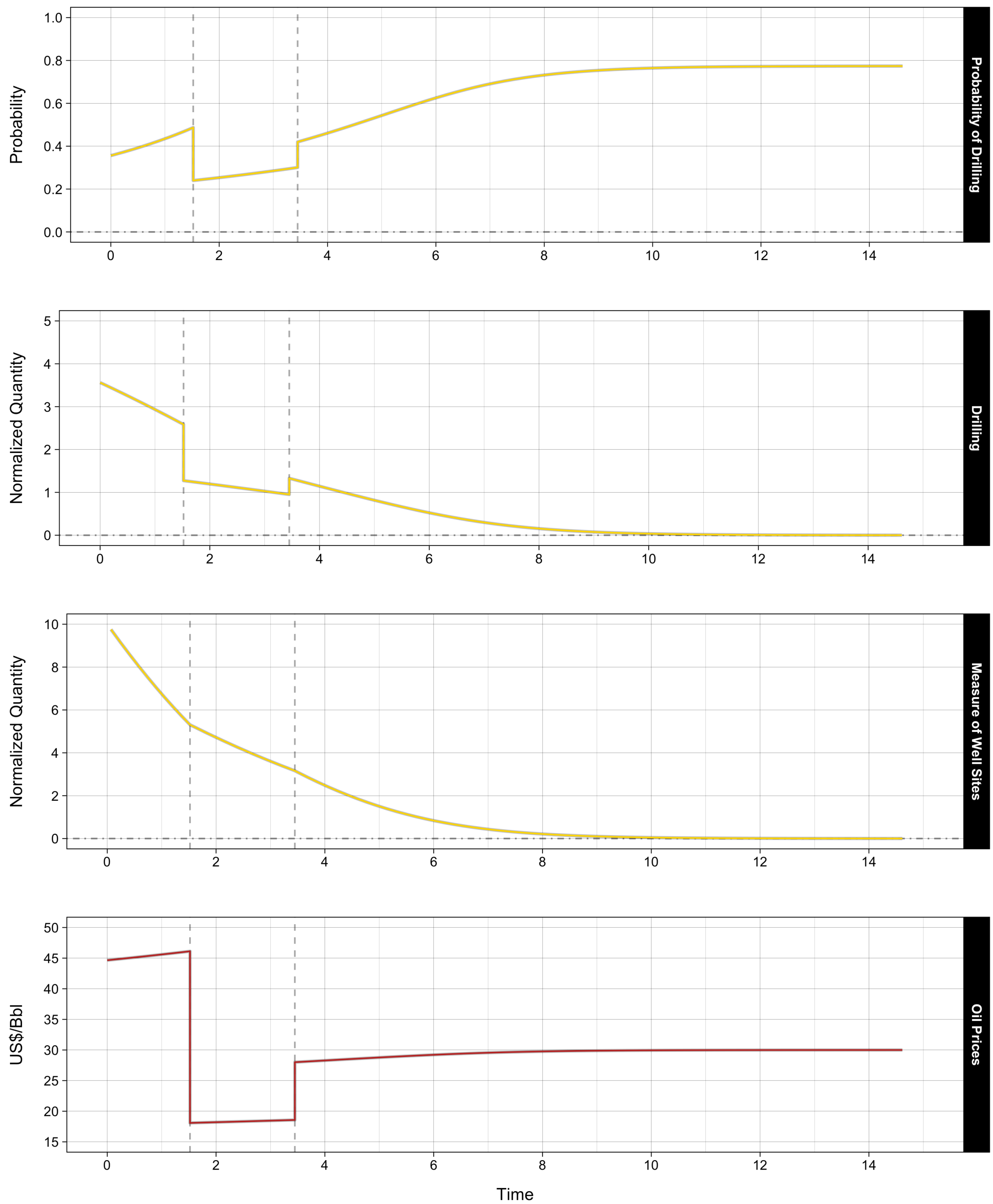

Figure 3.6: Equilibrium Paths under Unexpected Demand Shocks

Note: This figure shows the equilibrium paths of drilling probability, drilling, and the measure of well sites, which are obtained from a simulation for two unanticipated demand shocks. For these simulation results, we assume the identical parameter values and cost function utilized to draw the phase diagrams in Figure 3.5.

3.4 Equilibrium Dynamics with Oil Prices

This section examines how the time paths for optimal drilling and production vary with oil prices. Using the Implicit Function Theorem, we first predict the impact of a sudden price variation on the drilling probability, which governs the optimal paths of drilling and production. We then demonstrate how the optimal drilling and production paths respond to unexpected demand shocks. We also investigate the heterogeneous impacts of unanticipated demand shocks on drilling well sites of different quality. Finally, we compute the equilibrium paths under two different scenarios for oil prices: exogenous and endogenous oil prices.

3.4.1 Impacts of Unexpected Demand Shocks

The Implicit Function Theorem (IFT) allows us to predict the impact of sudden demand shocks on the equilibrium paths for drilling and production. Applying the IFT to equation (3.45) (i.e., the Euler equation of the firm's problem) yields

$$\frac{\partial Pr_k}{\partial p_k} = \left\{ \frac{\rho Pr_k(1 - Pr_k)}{\sigma(\lambda_a Pr_k + \rho)} \right\} \frac{\partial \psi_{i1k}}{\partial p_k}. \tag{3.46}$$

This resulting equation suggests that an unexpected positive price shock will lead to a higher drilling rate. The equation also shows that drilling is more responsive to prices when the relative importance of cost shocks, which is captured by the magnitude of σ, is small.

Figure 3.6 depicts how the paths of drilling probability, drilling, reserves, and oil price respond to two unanticipated demand shocks. The first negative demand shock causes drilling probability discontinuously decreases. Due to the reduction in drilling probability, drilling demonstrates a discontinuous decrease too. Moreover, the negative demand shock also reduces the depletion rate of the remaining well locations. As shown in the last panel in the figure, the oil price jumps down on impact after the negative demand shock, then gradually rises.[40] The later positive demand shock induces the opposite reactions in the equilibrium paths.

3.4.2 Heterogeneous Impacts of Unanticipated Demand Shocks on Drilling Well Sites of Different Quality

To examine how the firm's drilling activity at well sites of heterogeneous quality responds to unexpected demand shocks, we now assume that potential drilling locations can be of low quality,

[40] Drilling, and thus production, rapidly diminishes for a while after $t = 0$. Then, its rate of change gradually decreases, and drilling eventually converges to a lower bound. In other words, the time path of drilling has a convex profile. Because equation (3.21) determines the oil price at time t, the time path for the endogenous oil price is a concave curve.

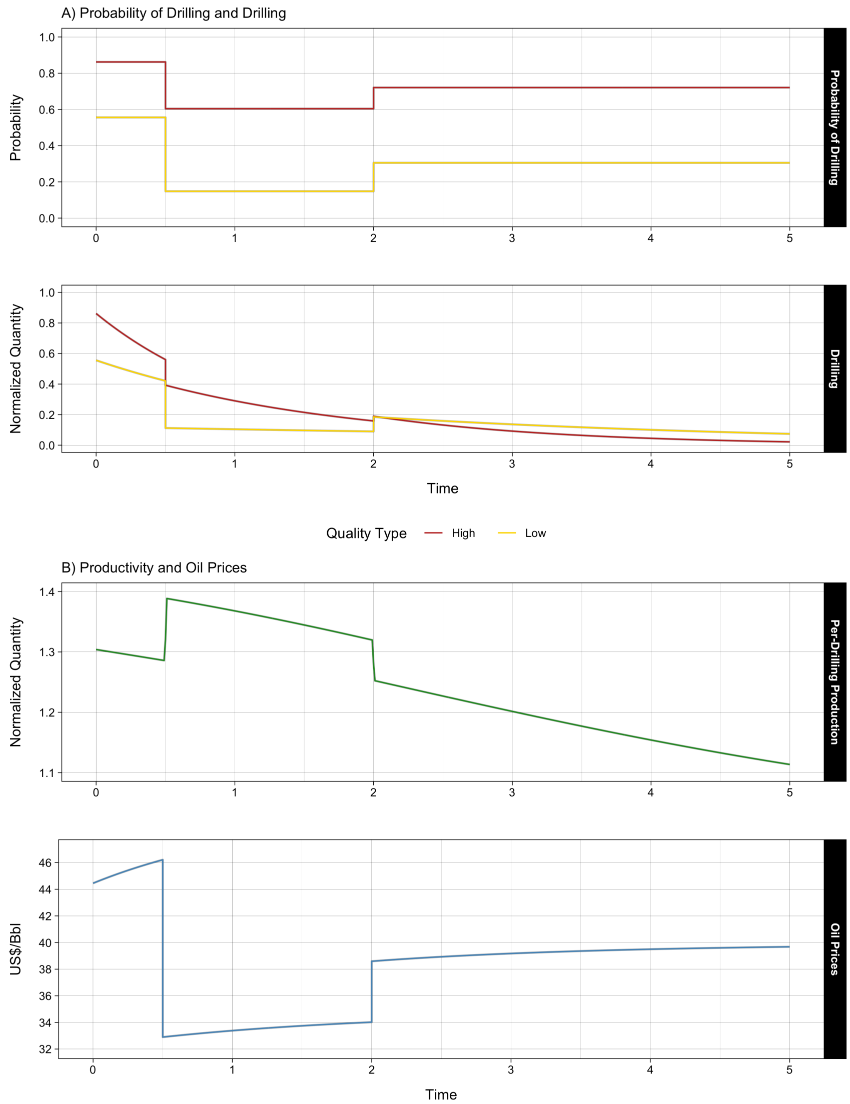

Figure 3.7: Heterogeneous Impacts of Unexpected Demand Shocks on Drilling and Production

Note: This figure shows how the firm's drilling activity at well sites of heterogeneous quality responds to unexpected demand shocks. As shown in the first panel, the drilling probability of low-quality well sites shows a higher sensitivity to the first negative demand shock. Although the drilling probability of low-quality well locations more sensitively responds to the second positive demand shock, the probability is still lower than that of high-quality well sites. The second panel demonstrates the time paths of drilling, corresponding to the drilling probabilities. The third panel illustrates the impacts of the demand shocks on oil extraction productivity. Clearly, the first negative shock discontinuously increases per-drilling oil production due to the high sensitivity of low-quality location drilling. To the second positive demand shock, the per-drilling production showed the opposite reaction. For this simulation, we assume that a dispersion parameter of $\sigma = 1$, a discount rate of $\rho = 0.05$, an initial number of well sites of $R_0^g = 1$, additional well sites of $E^g = 0$, where $g \in \{L, H\}$. Also, we assume that a flow payoff function of $f(p_k) = 1$ and that a choice-specific instantaneous payoff function of $\psi_{iak}(p_k) = 1.5p_k - 2$ for high-quality sites.

in which case a well's production is α^L or of high quality, in which case production is α^H ($> \alpha^L$). The firm's choice-specific instantaneous payoff is then $\psi_{i1k}(p_k) = \alpha^g p_k - c$, $g \in \mathcal{Q} = \{L, H\}$.[41]

Figure 3.7 illustrates the results from a simulation. As discussed in Section 3.2.2.2, our empirical analysis reveals that fracking firms in North Dakota more significantly reduced drilling at low-quality well sites, more than at the high-quality ones, when experiencing sharp oil price declines. The time paths for drilling and production presented in the figure clearly show that the model-predicted elasticity of drilling s greater on low-quality well sites, just as illustrated in Figure 3.3.[42] As demonstrated in the third panel of the figure, per-drilling production, i.e., productivity, increases discontinuously due to the negative demand shock. Consequently, as described in the fourth panel, per-drilling oil production is also improved.

3.4.3 Exogenous vs. Endogenous Oil Prices

This section examines the equilibrium path of drilling for each of the endogenous and exogenous oil prices. In the endogenous-price scenario, the market clearing oil price is determined from equation (3.21). Moreover, the exogenous price means the case of a constant oil price, in which the oil production industry is small relative to the world oil market.[43]

The Euler equation (3.45) allows us to predict the differences in drilling and production time paths between the two price scenarios. The endogenous price is lower than the exogenous price when there is oil production (i.e., $Q > 0$). In the Euler equation, a lower price, thus a lower instantaneous payoff of drilling (i.e., ψ_{i1k}), implies a lower probability of drilling. In other words, endogenizing the time path of oil prices makes the probability of drilling at time $t = 0$ decrease due to the initial production (i.e., $Q_0 > 0$). Since increasing drilling, and thus production, causes oil prices endogenously determined to fall, there would be no incentive to rapidly raise the rate of drilling. For these reasons, drilling under endogenous oil prices (denoted D_t^{en}) would be small relative to that under exogenous oil prices (denoted D_t^{ex}) for some period after $t = 0$. But at some time point, D_t^{en} would be larger than D_t^{ex} because of the lower level of undrilled reserves in the exogenous-price case. Figure 3.8, which shows the time paths for drilling and the remaining reserves for each type of oil price, supports the predictions.

[41] In the formulation, we implicitly normalize the oil production from a low-quality well location to 1.

[42] The term $Pr_k(1 - Pr_k)$ in equation (3.46) is a parabolic curve that goes to zero as Pr_k approaches to zero or one and that has its maximum value at $Pr_k = 1/2$. These properties of the term suggest the possibility that the drilling of high-quality well sites is less responsive to a demand shock.

[43] In other words, $\bar{p}_1 = 0$ in equation (3.21) in the exogenous-price scenario.

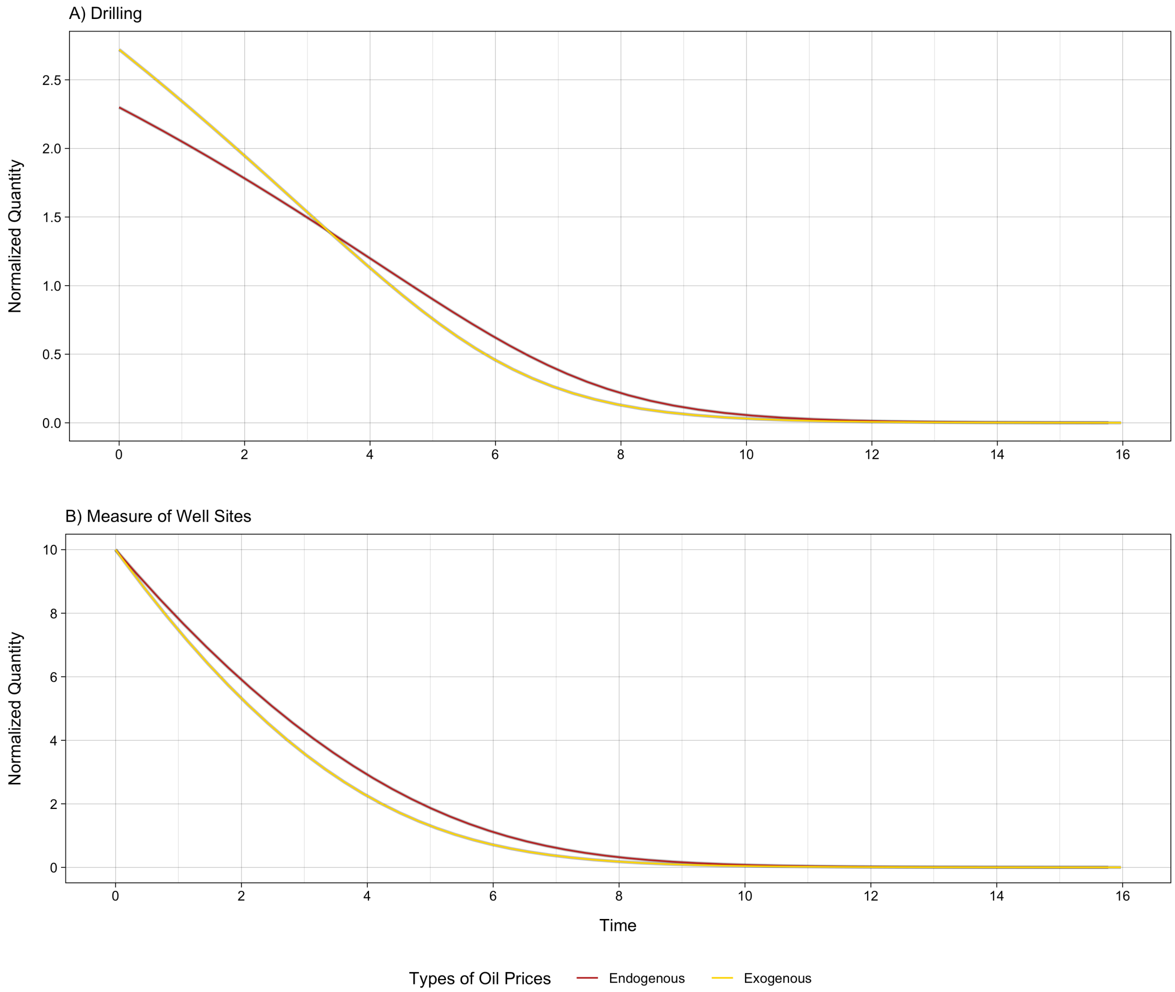

Figure 3.8: Time Paths under Endogenous and Exogenous Oil Prices

Note: This figure depicts differences in the time paths for drilling and the measure of well locations under endogenous and exogenous oil prices. This figure takes the assumptions exploited in Figure 3.5. See the text for details.

3.5 Conclusion

In this paper, we first present two interesting empirical findings about the drilling decisions of hydraulic fracturing companies in North Dakota. First, the oil producers drilled horizontal wells into sites of heterogeneous quality, not in a strict order, but simultaneously. Second, the drilling of low-quality well sites was more responsive to the significant plunge in oil prices in the second half of 2014 than that of high-quality ones.

We develop a continuous-time Discrete Choice Dynamic Programming (DCDP) to explain the empirical facts that are not captured in the economic models developed in other papers. Our theoretical framework is analytically tractable. Moreover, our economic model, in which choice-specific cost shocks at each decision opportunity allow us to avoid modeling specific constraints (e.g., capacity and transmission constraints), provides us with insightful implications for how the drilling activity of fracking firms operating in North Dakota evolves in response to oil price changes. Furthermore, in our model of optimal drilling, well-level drilling decisions naturally lead to the optimal firm-level path of drilling.

In addition to the analytical advantages, our model can also be estimable empirically. We can easily take our model to detailed well-level drilling and production data. Therefore, utilizing the empirically estimated values of structural parameters, we can perform counterfactual analysis on real-world issues in the oil and gas industry, such as a change in the severance tax rate in North Dakota. In other words, our theoretical framework can bridge Hotelling-style theoretical approaches with empirical research that relies heavily on microeconomic data.

Appendix A

Appendixes for Chapters

A.1 For Chapter 1

A.1.1 Additional Figure(s) and Table(s)

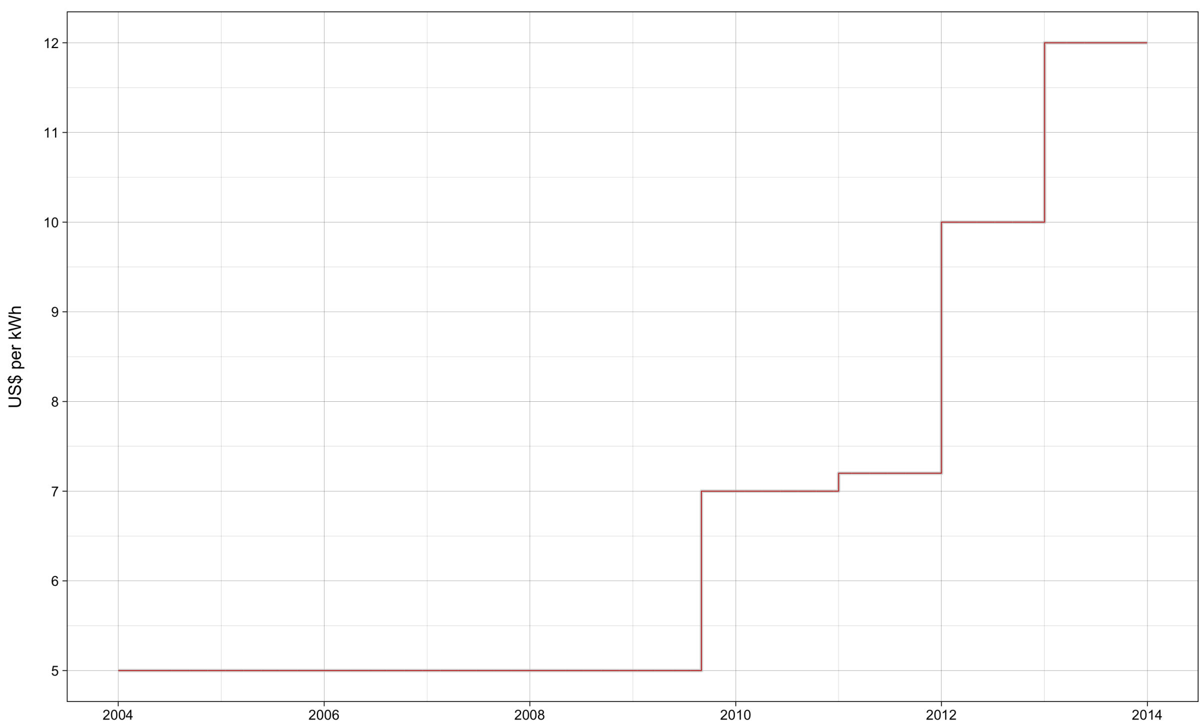

Figure A.1: Fixed Charge of SMUD Residential Rates

Note: The figure shows how SMUD changed the monthly fixed charge over time. The same fixed charge applies to households that choose one of the three major residential rate plans (i.e., RSCH, RSEH, and RSGH).

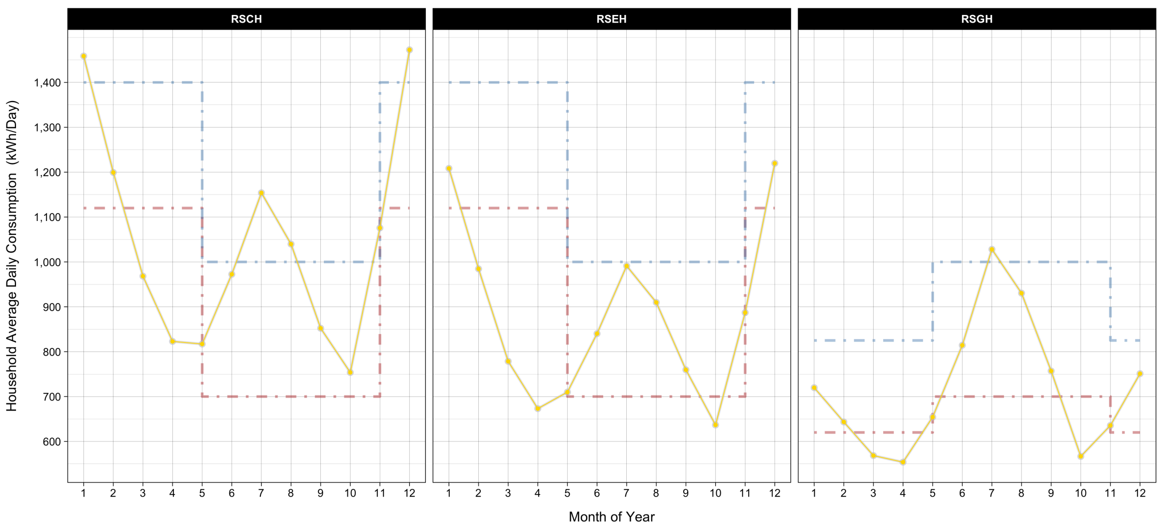

Figure A.2: Household Average Daily Electricity Consumption by Month of Year

Note: This figure depicts, for each of SMUD residential rate plans, how households' average daily electricity consumption varied across months of the year. The red and blue dot-dash lines represent the lower and higher base usage quantities in each month of the year, respectively. The three rate plans show similar consumption and seasonal patterns.

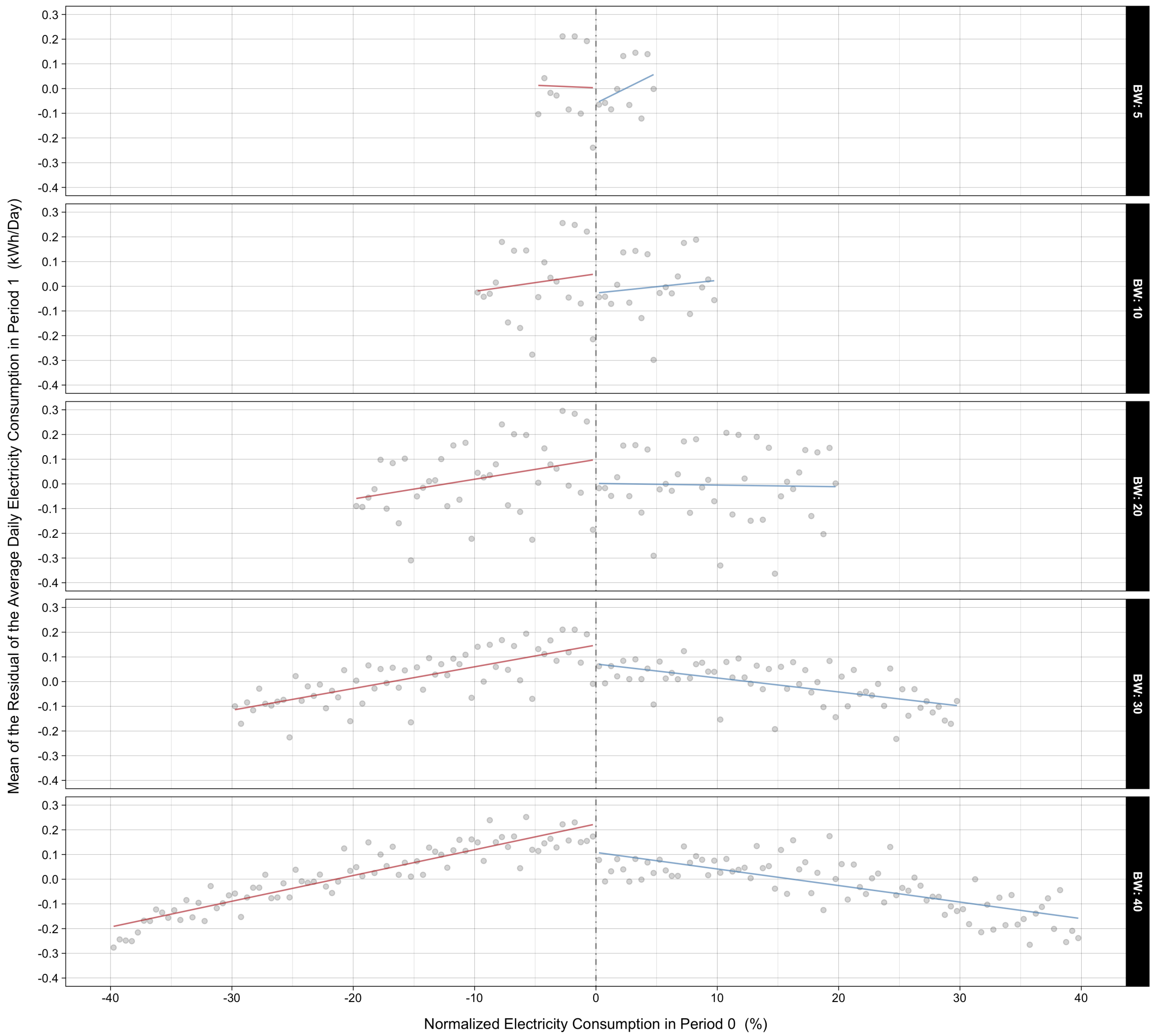

Figure A.3: The Impact of the Change in the Marginal Price due to Surpassing the Lower Base Usage Quantity

Note: In this figure, scatter dots correspond to the mean of residuals, computed by bins with a bandwidth of 0.5%, from a regression of households' average daily electricity consumption in Period 1 on $\overline{NC}_0$, HDDs and CDDs. As described, a linear model fits those scatter points well, even for a wide bandwidth.

Table A.1: Robustness Checks: For Different Functional Forms, 3rd- and 4th-Order Polynomial Models

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙[Treatment]	0.049	−0.022	−0.056***	−0.101***	0.129**	0.019	−0.049**	−0.068**
	(0.042)	(0.025)	(0.017)	(0.028)	(0.051)	(0.037)	(0.021)	(0.027)
NC0	0.143***	0.211***	0.215***	0.225***	0.111**	0.207***	0.213***	0.217***
	(0.022)	(0.010)	(0.006)	(0.010)	(0.043)	(0.016)	(0.008)	(0.011)
𝟙[Treatment] × NC0	0.056	0.005	−0.007	0.0003	−0.035	−0.027	−0.008	−0.001
	(0.035)	(0.013)	(0.005)	(0.005)	(0.079)	(0.021)	(0.008)	(0.010)
$NC0^2$	−0.020***	−0.002	−0.0003	−0.0001	−0.035**	−0.003	−0.001	−0.001*
	(0.005)	(0.001)	(0.0002)	(0.0002)	(0.017)	(0.003)	(0.001)	(0.001)
𝟙[Treatment] × $NC0^2$	0.022***	0.001	0.0004	−0.0004	0.092***	0.010**	0.001	0.001**
	(0.008)	(0.001)	(0.0003)	(0.0003)	(0.024)	(0.005)	(0.001)	(0.001)
$NC0^3$	−0.001***	−0.00005	−0.00000	0.00000	−0.004	−0.0001	−0.00002	−0.00003*
	(0.0003)	(0.00003)	(0.00001)	(0.00000)	(0.002)	(0.0002)	(0.00004)	(0.00002)
𝟙[Treatment] × $NC0^3$	0.001**	0.0001	−0.00000	0.00000	−0.005	−0.0005*	−0.00001	−0.00000
	(0.001)	(0.00005)	(0.00001)	(0.00001)	(0.005)	(0.0003)	(0.0001)	(0.00004)
$NC0^4$					−0.0001	−0.00000	−0.00000	−0.00000*
					(0.0001)	(0.00000)	(0.00000)	(0.00000)
𝟙[Treatment] × $NC0^4$					0.001***	0.00002*	0.00000	0.00000**
					(0.0002)	(0.00001)	(0.00000)	(0.00000)
Average Daily CDDs	1.146***	1.146***	1.135***	1.133***	1.146***	1.146***	1.135***	1.133***
	(0.106)	(0.105)	(0.109)	(0.129)	(0.106)	(0.105)	(0.109)	(0.129)
Average Daily HDDs	0.428***	0.431***	0.375***	0.742***	0.428***	0.431***	0.375***	0.742***
	(0.106)	(0.104)	(0.128)	(0.202)	(0.106)	(0.104)	(0.128)	(0.202)
Bandwidth	10%	20%	30%	40%	10%	20%	30%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,378,864	4,702,081	6,276,579	3,904,120	2,378,864	4,702,081	6,276,579	3,904,120
Adjusted R^2	0.293	0.334	0.536	0.592	0.293	0.334	0.536	0.592

Note: This table reports the results of robustness checks for different functional forms, specifically the third- and fourth-order polynomial models. Standard errors in parentheses are clustered at the household and billing year-by-month levels; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.2: Robustness Checks: For Different Bandwidths, Without FEs

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$[Treatment]	-0.014	-0.054^{*}	-0.053^{*}	-0.084^{***}	-0.076^{***}	-0.072^{**}	-0.097^{*}	-0.118^{*}
	(0.032)	(0.030)	(0.028)	(0.028)	(0.029)	(0.031)	(0.056)	(0.064)
NC0	0.169^{***}	0.197^{***}	0.202^{***}	0.204^{***}	0.204^{***}	0.199^{***}	0.214^{***}	0.211^{***}
	(0.010)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)
$\mathbb{1}$[Treatment] × NC0	0.038^{***}	0.001	-0.010^{***}	-0.008^{***}	-0.009^{***}	-0.014^{***}	-0.018^{***}	-0.017^{***}
	(0.012)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Average Daily CDDs	0.749^{***}	0.753^{***}	0.755^{***}	0.757^{***}	0.758^{***}	0.767^{***}	0.932^{***}	1.143^{***}
	(0.122)	(0.121)	(0.120)	(0.119)	(0.118)	(0.114)	(0.124)	(0.124)
Average Daily HDDs	0.280^{***}	0.281^{***}	0.282^{***}	0.284^{***}	0.286^{***}	0.152^{**}	0.637^{***}	1.033^{***}
	(0.079)	(0.078)	(0.078)	(0.077)	(0.077)	(0.066)	(0.101)	(0.131)
(Constant)	19.947^{***}	19.973^{***}	19.972^{***}	19.965^{***}	19.937^{***}	19.720^{***}	17.769^{***}	15.117^{***}
	(0.948)	(0.941)	(0.937)	(0.932)	(0.926)	(0.829)	(1.082)	(1.159)
Bandwidth	5%	10%	15%	20%	25%	30%	35%	40%
FEs: Billing Year-by-Month	No	No	No	No	No	No	No	No
Observations	1,186,630	2,378,864	3,566,318	4,702,081	5,816,854	6,276,579	4,093,259	3,904,120
Adjusted R^2	0.105	0.120	0.144	0.175	0.210	0.349	0.394	0.468

Note: Contrary to Table 1.3, this table reports the results of robustness checks for a range of bandwidths using the regression in the specification (5) in Table 1.2. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.3: Robustness Checks: For Different Bandwidths, Only RSGH Rate Code

	Dependent Variable							
	Average Daily Electricity Consumption (kWh/Day)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$[Treatment]	−0.055***	−0.060***	−0.055***	−0.065***	−0.064***	−0.058***	−0.068***	−0.080***
	(0.020)	(0.016)	(0.015)	(0.014)	(0.013)	(0.013)	(0.021)	(0.024)
NC0	0.211***	0.215***	0.215***	0.216***	0.216***	0.217***	0.234***	0.229***
	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)	(0.010)
$\mathbb{1}$[Treatment] × NC0	−0.005	−0.010***	−0.013***	−0.012***	−0.014***	−0.016***	−0.021***	−0.020***
	(0.006)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Average Daily CDDs	1.170***	1.172***	1.174***	1.174***	1.172***	1.171***	1.162***	1.190***
	(0.106)	(0.108)	(0.108)	(0.107)	(0.107)	(0.106)	(0.114)	(0.126)
Average Daily HDDs	0.224**	0.227**	0.227**	0.228**	0.228**	0.229**	0.547***	0.708***
	(0.090)	(0.090)	(0.090)	(0.089)	(0.088)	(0.087)	(0.133)	(0.186)
Rate Code	RSGH	RSGH	RSGH	RSGH	RSGH	RSGH	RSGH	RSGH
Bandwidth	5%	10%	15%	20%	25%	30%	35%	40%
FEs: Billing Year-by-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	967,546	1,941,332	2,909,164	3,832,683	4,738,070	5,604,830	3,396,312	3,191,411
Adjusted R^2	0.475	0.486	0.503	0.524	0.547	0.571	0.576	0.613

Note: This table shows the results of regressions with observations only for households selecting the RSGH rate plan. Standard errors in parentheses are clustered at the household and billing year-by-month levels to allow correlations across households in a given month; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

A.2 For Chapter 2

A.2.1 Additional Figure(s) and Table(s)

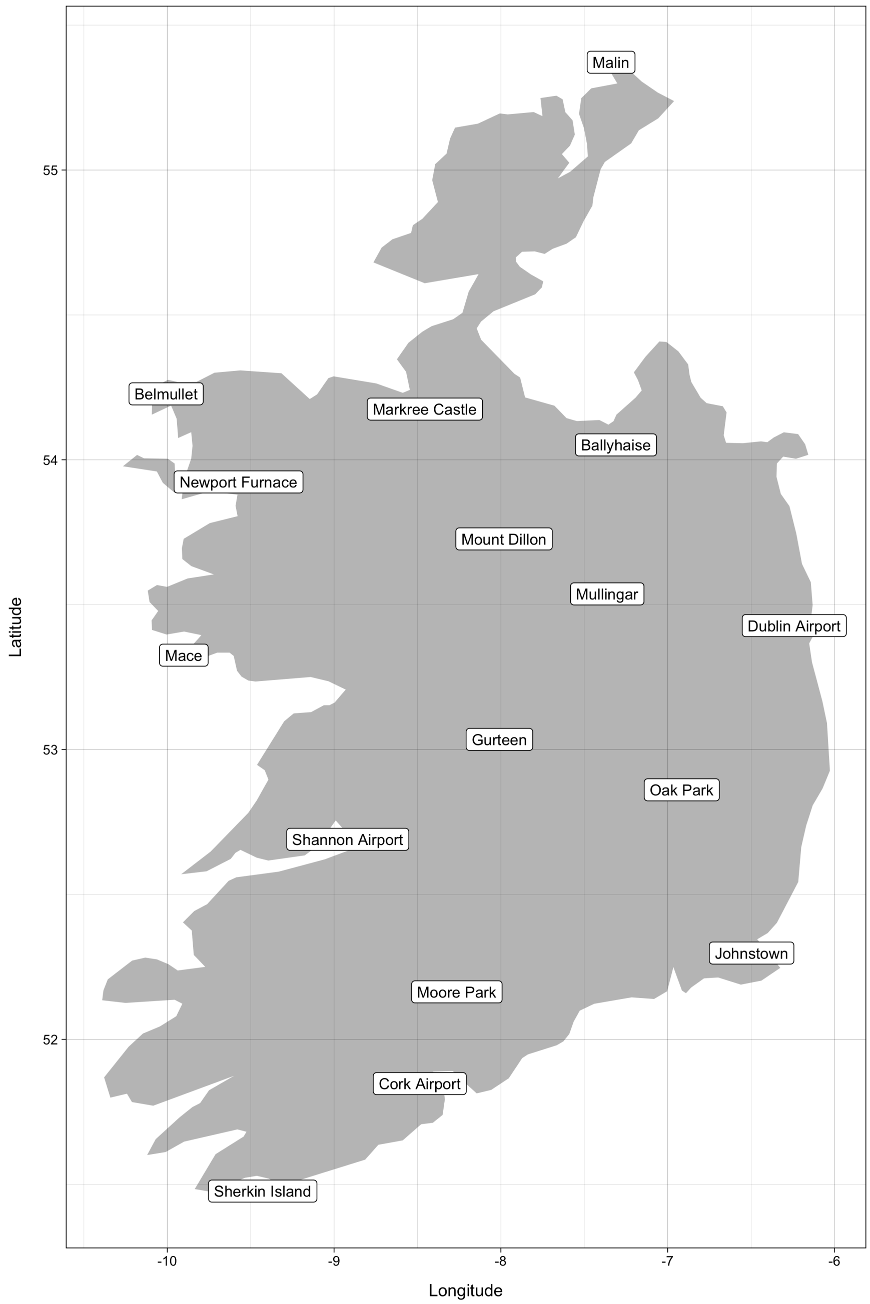

Figure A.4: Weather Stations from which Historical Weather Data have been collected

Note: This figure demonstrates the location of each weather station listed in Table A.4. As is evident from the map, the weather stations are distributed throughout Ireland.

Table A.4: Correlations in Average Daily Temperatures between Weather Stations

Stations	Correlation Coefficients	
	For Sample Period	For Experiment Period
Ballyhaise	0.98291	0.98244
Belmullet	0.96089	0.96361
Cork Airport	0.97121	0.97130
Gurteen	0.98389	0.98307
Johnstown	0.98189	0.97958
Mace	0.95870	0.95921
Malin	0.95632	0.95705
Markree Castle	0.97194	0.97179
Moore Park	0.98057	0.97798
Mount Dillon	0.97945	0.97782
Mullingar	0.98876	0.98654
Newport Furnace	0.97015	0.97211
Oak Park	0.99074	0.98925
Shannon Airport	0.97696	0.97582
Sherkin Island	0.95342	0.95411

Note: For each weather station, historical weather data from the weather station at Dublin airport is utilized to compute the two correlation coefficients. The location of each weather station stated in the table is shown on a map in Figure A.4. I do not provide the p-value of each correlation coefficient because it is arbitrarily small in magnitude. And the experiment period is the period between July 2009 to December 2010, while the sample period is the second half of 2009 and 2010.

Table A.5: Hourly Average Treatment Effects in and near the Peak Rate Period

	Hourly Electricity Consumption (kWh/Hour)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
𝟙[Treatment & Post]	−0.048***	−0.053*	−0.002	−0.049	−0.125***	−0.161***	−0.119***	−0.249***	−0.082***	−0.055*	−0.015	−0.113**
	(0.016)	(0.027)	(0.017)	(0.031)	(0.020)	(0.036)	(0.022)	(0.044)	(0.020)	(0.030)	(0.021)	(0.048)
Description of Period	Pre-Peak	Pre-Peak	Pre-Peak	Pre-Peak	Peak	Peak	Peak	Peak	Post-Peak	Post-Peak	Post-Peak	Post-Peak
Period of Hours	15 to 16	15 to 16	15 to 16	15 to 16	17 to 18	17 to 18	17 to 18	17 to 18	19 to 20	19 to 20	19 to 20	19 to 20
Tariff Group	A	B	C	D	A	B	C	D	A	B	C	D
Price Change in the Peak Rate Period	+6	+12	+18	+24	+6	+12	+18	+24	+6	+12	+18	+24
FEs: Household by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FEs: Month of Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	506,540	326,800	511,700	331,960	506,540	326,800	511,700	331,960	506,540	326,800	511,700	331,960
Adjusted R^2	0.312	0.330	0.320	0.327	0.384	0.397	0.383	0.367	0.371	0.389	0.376	0.361

Note: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.6: Breakdown of Hourly Average Treatment Effects

	Hourly Electricity Consumption (kWh/Hour)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HDDs	0.016***	0.016***	0.016***	0.015***	0.047***	0.047***	0.047***	0.047***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
HDDs*	0.010	0.009	0.009	0.010	−0.018***	−0.018***	−0.018***	−0.018***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
𝟙[Treatment]	0.009	0.106	−0.014	0.174**	0.057	0.189**	−0.017	0.150**
	(0.050)	(0.071)	(0.049)	(0.072)	(0.055)	(0.083)	(0.052)	(0.072)
𝟙[Treatment] × HDDs	0.001	0.004	0.001	0.0003	0.009**	0.008	0.008**	0.011
	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)	(0.007)	(0.004)	(0.007)
𝟙[Treatment] × HDDs*	−0.0001	−0.012*	0.0004	0.002	−0.012***	−0.016**	−0.013***	−0.008
	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.008)	(0.004)	(0.007)
𝟙[Post]	0.014	0.015	0.014	0.011	0.048	0.049	0.047	0.047
	(0.022)	(0.022)	(0.022)	(0.023)	(0.040)	(0.040)	(0.040)	(0.040)
𝟙[Post] × HDDs	−0.007	−0.007	−0.007	−0.006	−0.015**	−0.015**	−0.015**	−0.015**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
𝟙[Post] × HDDs*	0.002	0.002	0.002	0.001	0.006	0.007	0.006	0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)

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Table A.6 – continued from previous page

	Hourly Electricity Consumption (kWh/Hour)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$[Treatment & Post]	−0.038	−0.039	0.020	−0.039	−0.040	−0.050	0.006	−0.025
	(0.023)	(0.030)	(0.026)	(0.038)	(0.029)	(0.037)	(0.027)	(0.040)
$\mathbb{1}$[Treatment & Post] × HDDs	0.001	−0.003	−0.0002	0.001	−0.003	0.0005	0.0003	−0.009
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)	(0.006)
$\mathbb{1}$[Treatment & Post] × HDDs*	−0.002	0.008	−0.004	−0.005	0.005	0.010	0.004	0.008
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.007)	(0.003)	(0.006)
Description of Period	Pre-Peak	Pre-Peak	Pre-Peak	Pre-Peak	Post-Peak	Post-Peak	Post-Peak	Post-Peak
Period of Hours	15 to 16	15 to 16	15 to 16	15 to 16	19 to 20	19 to 20	19 to 20	19 to 20
Tariff Group	A	B	C	D	A	B	C	D
Price Change in the Peak Rate Period	+6	+12	+18	+24	+6	+12	+18	+24
Knot	10	10	10	10	10	10	10	10
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	506,540	326,800	511,700	331,960	506,540	326,800	511,700	331,960
Adjusted R^2	0.024	0.024	0.023	0.025	0.041	0.040	0.039	0.043

Note: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.7: Hourly Treatment Effects as a Linear Function of Peak-Rate-Period Price Changes

	Hourly Electricity Consumption (kWh/Hour)					
	(1)	(2)	(3)	(4)	(5)	(6)
HDDs	0.016***	0.042***	0.047***	0.016***	0.042***	0.047***
	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.005)
HDDs*	0.010	0.001	−0.018***	0.010	0.001	−0.018**
	(0.007)	(0.010)	(0.007)	(0.007)	(0.010)	(0.007)
$\mathbb{1}$[Treatment]	−0.020	−0.018	0.064			
	(0.059)	(0.073)	(0.065)			
$\mathbb{1}$[Treatment] × ΔPC	0.004	0.005	−0.0003			
	(0.003)	(0.004)	(0.003)			
$\mathbb{1}$[Treatment] × HDDs	0.001	0.013**	0.009	0.001	0.013**	0.009
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
$\mathbb{1}$[Treatment] × HDDs*	−0.003	−0.011*	−0.014***	−0.003	−0.011	−0.014**
	(0.005)	(0.006)	(0.005)	(0.006)	(0.007)	(0.007)
$\mathbb{1}$[Treatment] × HDDs × ΔPC	−0.00001	−0.0004	0.00003	−0.00001	−0.0004	0.00003
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
$\mathbb{1}$[Treatment] × HDDs* × ΔPC	0.0001	0.0003	0.0001	0.0001	0.0003	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
$\mathbb{1}$[Post]	0.013	0.045	0.047	0.013	0.045	0.047
	(0.022)	(0.036)	(0.040)	(0.024)	(0.038)	(0.042)
$\mathbb{1}$[Post] × HDDs	−0.007	−0.015*	−0.015**	−0.007	−0.015*	−0.015**
	(0.005)	(0.008)	(0.006)	(0.005)	(0.008)	(0.006)
$\mathbb{1}$[Post] × HDDs*	0.002	0.007	0.006	0.002	0.007	0.006
	(0.008)	(0.013)	(0.009)	(0.008)	(0.014)	(0.010)
$\mathbb{1}$[Treatment & Post]	−0.045	−0.028	−0.053	−0.045	−0.028	−0.053
	(0.029)	(0.035)	(0.035)	(0.032)	(0.039)	(0.038)

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Table A.7 – continued from previous page

	Hourly Electricity Consumption (kWh/Hour)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$[Treatment & Post] × ΔPC	0.002	−0.005**	0.002	0.002	−0.005**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\mathbb{1}$[Treatment & Post] × HDDs	−0.0001	−0.010**	−0.001	−0.0001	−0.010*	−0.001
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)
$\mathbb{1}$[Treatment & Post] × HDDs*	0.001	0.012**	0.005	0.001	0.012	0.005
	(0.005)	(0.006)	(0.005)	(0.007)	(0.008)	(0.007)
$\mathbb{1}$[Treatment & Post] × HDDs × ΔPC	0.00001	0.0002	−0.0001	0.00001	0.0002	−0.0001
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
$\mathbb{1}$[Treatment & Post] × HDDs* × ΔPC	−0.0002	−0.0003	0.00004	−0.0002	−0.0003	0.00004
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Description of Period	Pre-Peak	Peak	Post-Peak	Pre-Peak	Peak	Post-Peak
Period of Hours	15 to 16	17 to 18	19 to 20	15 to 16	17 to 18	19 to 20
Knot	10	10	10	10	10	10
FEs: Household	No	No	No	Yes	Yes	Yes
FEs: Day of Week by Half-Hourly Time Window	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,006,200	1,006,200	1,006,200	1,006,200	1,006,200	1,006,200
Adjusted R^2	0.024	0.047	0.040	0.288	0.343	0.356

Note: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

A.3 For Chapter 3

A.3.1 Details in Derivations

A.3.1.1 Linearization near the Steady State of the Social Planner's Problem

Using a Taylor series expansion, $\dot{R}_t$ can be approximated near the steady state $(R_{ss},\, \pi_{ss})$:

$$\begin{aligned}
\dot{R}_t \;&\approx\; (-\lambda_a R_{ss} Pr_{ss} \;+\; E) \\
&\qquad +\; \frac{\partial}{\partial R_t}(-\lambda_a R_t Pr_t \;+\; E)(R_t \;-\; R_{ss}) \;+\; \frac{\partial}{\partial \pi_t}(-\lambda_a R_t Pr_t \;+\; E)(\pi_t \;-\; \pi_{ss}) \\
&= 0 \;+\; \lambda_a \left(-Pr_t \;-\; \frac{\partial Pr_t}{\partial R_t} R_t\right)(R_t \;-\; R_{ss}) \;+\; \lambda_a \left(-\frac{\partial Pr_t}{\partial \pi_t} R_t\right)(\pi_t \;-\; \pi_{ss}) \\
&= \lambda_a \left(-Pr_t \;-\; \frac{\partial Pr_t}{\partial R_t} R_t\right)(R_t \;-\; R_{ss}) \;+\; \lambda_a \left(-\frac{\partial Pr_t}{\partial \pi_t} R_t\right)(\pi_t \;-\; \pi_{ss}).
\end{aligned}$$

In the same way, the linear approximation of $\dot{\pi}_t$ near the steady state $(R_{ss},\, \pi_{ss})$ is given by

$$\begin{aligned}
\dot{\pi}_t \;&\approx\; \big(r\pi_{ss} \;-\; \lambda_a \sigma\big(\gamma \;-\; \ln(1 - Pr_{ss})\big)\big) \\
&\qquad +\; \frac{\partial}{\partial R_t}\left(r\pi_t \;-\; \lambda_a \sigma\big(\gamma \;-\; \ln(1 - Pr_t)\big)\right)(R_t \;-\; R_{ss}) \\
&\qquad +\; \frac{\partial}{\partial \pi_t}\left(r\pi_t \;-\; \lambda_a \sigma\big(\gamma \;-\; \ln(1 - Pr_t)\big)\right)(\pi_t \;-\; \pi_{ss}) \\
&= 0 \;+\; \left(-\frac{\lambda_a \sigma}{1 - Pr_t}\frac{\partial Pr_t}{\partial R_t}\right)(R_t \;-\; R_{ss}) \;+\; \left(r \;-\; \frac{\lambda_a \sigma}{1 - Pr_t}\frac{\partial Pr_t}{\partial \pi_t}\right)(\pi_t \;-\; \pi_{ss}) \\
&= \lambda_a \left(-\frac{\sigma}{1 - Pr_t}\frac{\partial Pr_t}{\partial R_t}\right)(R_t \;-\; R_{ss}) \;+\; \lambda_a \left(\frac{r}{\lambda_a} \;-\; \frac{\sigma}{1 - Pr_t}\frac{\partial Pr_t}{\partial \pi_t}\right)(\pi_t \;-\; \pi_{ss}).
\end{aligned}$$

From those two approximations, the linearized system near the steady state $(R_{ss},\, \pi_{ss})$ is

$$\begin{aligned}
\begin{pmatrix} \dot{R}_t \\ \dot{\pi}_t \end{pmatrix} \;&=\; \lambda_a \begin{pmatrix} -Pr_t \;-\; \frac{\partial Pr_t}{\partial R_t} R_t & -\frac{\partial Pr_t}{\partial \pi_t} R_t \\ -\frac{\sigma}{1-Pr_t}\frac{\partial Pr_t}{\partial R_t} & \frac{r}{\lambda_a} \;-\; \frac{\sigma}{1-Pr_t}\frac{\partial Pr_t}{\partial \pi_t} \end{pmatrix} \begin{pmatrix} R_t \;-\; R_{ss} \\ \pi_t \;-\; \pi_{ss} \end{pmatrix} \\
&=\; \lambda_a \begin{pmatrix} [1] & [2] \\ [3] & [4] \end{pmatrix} \begin{pmatrix} R_t \;-\; R_{ss} \\ \pi_t \;-\; \pi_{ss} \end{pmatrix}.
\end{aligned}$$

Applying the Implicit Function Theorem to necessary condition (3.35), we can obtain the followings:

$$\begin{cases}
\dfrac{\partial Pr_t}{\partial R_t} \;=\; -\dfrac{\big(\alpha^2 u''(\lambda_a \alpha R_t Pr_t) - c''(\lambda_a R_t Pr_t)\big)\lambda_a Pr_t}{\big(\alpha^2 u''(\alpha \lambda_a R_t Pr_t) - c''(\lambda_a R_t Pr_t)\big)\lambda_a R_t \;-\; \frac{\sigma}{Pr_t(1-Pr_t)}} \\[2ex]
\dfrac{\partial Pr_t}{\partial \pi_t} \;=\; \dfrac{1}{\big(\alpha^2 u''(\alpha \lambda_a R_t Pr_t) - c''(\lambda_a R_t Pr_t)\big)\lambda_a R_t \;-\; \frac{\sigma}{Pr_t(1-Pr_t)}}
\end{cases}$$

Because $\alpha^2 u''(\alpha \lambda_a R_t Pr_t) - c''(\lambda_a R_t Pr_t) < 0$ in our setting, $\partial Pr_t/\partial R_t < 0$ and $\partial Pr_t/\partial \pi_t < 0$.

In the coefficient matrix,

$$
\begin{aligned}
&[1] \;:\; -Pr_t \;-\; \frac{\partial Pr_t}{\partial R_t} R_t \;=\; \frac{\frac{\sigma}{Pr_t(1-Pr_t)}}{\big(\alpha^2 u''(\alpha\lambda_a R_t Pr_t) - c''(\lambda_a R_t Pr_t)\big)\lambda_a R_t \;-\; \frac{\sigma}{Pr_t(1-Pr_t)}} \;<\; 0;\\
&[2] \;:\; -\frac{\partial Pr_t}{\partial \pi_t} R_t \;>\; 0;\\
&[3] \;:\; -\frac{\sigma}{1-Pr_t}\frac{\partial Pr_t}{\partial R_t} \;>\; 0;\ \text{and}\\
&[4] \;:\; \frac{r}{\lambda_a} \;-\; \frac{\sigma}{1-Pr_t}\frac{\partial Pr_t}{\partial \pi_t} \;>\; 0.
\end{aligned}
$$

Therefore, the determinant of the coefficient matrix clearly has a negative value (i.e., $[1] \times [4] - [2] \times [3] < 0$).

A.3.1.2 The Value Function for a Well Site i in state k in Continuous Time

In our framework, the instantaneous Bellman equation can be approximated as follows:

$$
\begin{aligned}
(1+\tau\rho)V_{ik}(t) \;\approxeq\; & \tau f_{ik}\\
& +\; \tau\lambda_a E\Big[\max_{a\in\mathcal{A}}\big\{V_{i,\ell(i,a,k)}(t+\tau) \;+\; \psi_{iak} \;+\; \epsilon_{iak}\big\}\Big]\\
& +\; \sum_{\ell\neq k}\tau\lambda_{k\ell}V_{i\ell}(t+\tau)\\
& +\; \left\{1 \;-\; \tau\left(\lambda_a \;+\; \sum_{\ell\neq k}\lambda_{k\ell}\right)\right\} V_{ik}(t+\tau),
\end{aligned}
$$

where $1+\tau\rho$ is the discount factor for the time increment τ, $\tau\lambda_a$ is the probability that the firm in state k choose an action a in an incremental time period τ, and $\sum_{\ell\neq k}\tau\lambda_{k\ell}$ is the probability of moving from state k to state ℓ. The curly bracket of the fourth line in the expression, therefore, means the probability that the firm remains at state k.

Rearranging terms, dividing by τ, and letting $\tau \to 0$ yield a simpler expression:

$$
\begin{aligned}
&- \left\{V_{ik}(t+\tau) \;+\; V_{ik}(t)\right\} \;+\; \tau\rho V_{ik}(t) \;+\; \tau\left(\lambda_a \;+\; \sum_{\ell\neq k}\lambda_{k\ell}\right)V_{ik}(t+\tau) \\
&\qquad \approxeq\; \tau f_{ik} \;+\; \tau\lambda_a E\Big[\max_{a\in\mathcal{A}}\left\{V_{i,\ell(i,a,k)}(t+\tau) \;+\; \psi_{iak} \;+\; \epsilon_{iak}\right\}\Big] \;+\; \sum_{\ell\neq k}\tau\lambda_{k\ell}V_{i\ell}(t+\tau) \\
&- \frac{1}{\tau}\left\{V_{ik}(t+\tau) \;+\; V_{ik}(t)\right\} \;+\; \rho V_{ik}(t) \;+\; \left(\lambda_a \;+\; \sum_{\ell\neq k}\lambda_{k\ell}\right)V_{ik}(t+\tau) \\
&\qquad \approxeq\; f_{ik} \;+\; \lambda_a E\Big[\max_{a\in\mathcal{A}}\left\{V_{i,\ell(i,a,k)}(t+\tau) \;+\; \psi_{iak} \;+\; \epsilon_{iak}\right\}\Big] \;+\; \sum_{\ell\neq k}\lambda_{k\ell}V_{i\ell}(t+\tau) \\
&- \dot{V}_{ik}(t) \;+\; \left(\rho \;+\; \lambda_a \;+\; \sum_{\ell\neq k}\lambda_{k\ell}\right)V_{ik}(t) \\
&\qquad =\; f_{ik} \;+\; \lambda_a E\Big[\max_{a\in\mathcal{A}}\left\{V_{i,\ell(i,a,k)}(t) \;+\; \psi_{iak} \;+\; \epsilon_{iak}\right\}\Big] \;+\; \sum_{\ell\neq k}\lambda_{k\ell}V_{i\ell}(t).
\end{aligned}
$$

The assumption that the firm i's drilling decisions have no impact on the price of oil in the market (i.e., $\ell(i,a,k) = k$ for any $a \in \mathcal{A}$) yields an even simpler expression:

$$
\begin{aligned}
&- \dot{V}_{ik}(t) \;+\; \left(\rho \;+\; \lambda_a \;+\; \sum_{\ell\neq k}\lambda_{k\ell}\right)V_{ik}(t) \\
&\qquad =\; f_{ik} \;+\; \lambda_a E\Big[\max_{a\in\mathcal{A}}\left\{V_{ik}(t) \;+\; \psi_{iak} \;+\; \epsilon_{iak}\right\}\Big] \;+\; \sum_{\ell\neq k}\lambda_{k\ell}V_{i\ell}(t).
\end{aligned}
$$

A.3.1.3 The Euler Equation for the Firm's Problem

The assumption of no exogenous demand shock suggests that $\lambda_{k\ell} = 0$, for all ℓ. Under this assumption, the firm's value function, which is presented in equation (3.42), is simplified as follows:

$$
-\dot{V}_{ik}(t) \;+\; (\rho \;+\; \lambda_a)V_{ik}(t) \;=\; f_{ik} \;+\; \lambda_a E\Big[\max_{a\in\mathcal{A}}\left\{V_{ik}(t) \;+\; \psi_{iak} \;+\; \epsilon_{iak}\right\}\Big]
$$

In addition, equation (3.44) allows yielding the even simpler functional form of the firm's value function. When $a = 0$,

$$
V_{ik}(t) \;=\; \frac{\dot{V}_{ik}(t) \;+\; f_{ik} \;+\; \lambda_a\sigma\big(\gamma \;-\; \ln(1 - Pr_k)\big)}{\rho}.
$$

In the case of $a = 1$,

$$
V_{ik}(t) \;=\; \frac{\dot{V}_{ik}(t) \;+\; f_{ik} \;+\; \lambda_a\left\{\psi_{i1k} \;+\; \sigma\big(\gamma \;-\; \ln(Pr_k)\big)\right\}}{\rho \;+\; \lambda_a}.
$$

Equating the two equations, with some algebra, allows us having the Euler equation:

$$\frac{\dot{V}_{ik}(t) \ + \ f_{ik} \ + \ \lambda_a \sigma\big(\gamma \ - \ \ln(1 - Pr_k)\big)}{\rho} \ = \ \psi_{i1k} \ + \ \sigma\big(\gamma \ - \ \ln(Pr_k)\big) \ - \ \sigma\big(\gamma \ - \ \ln(1 - Pr_k)\big).$$

Similarly, $V_{ik}(t)$ can be expressed without $\dot{V}_{ik}(t)$ as follows:

$$V_{ik}(t) \ = \ \psi_{i1k} \ + \ \sigma\big(\gamma \ - \ \ln(Pr_k)\big) \ - \ \sigma\big(\gamma \ - \ \ln(1 - Pr_k)\big).$$

A.3.2 Additional Figure(s) and Table(s)

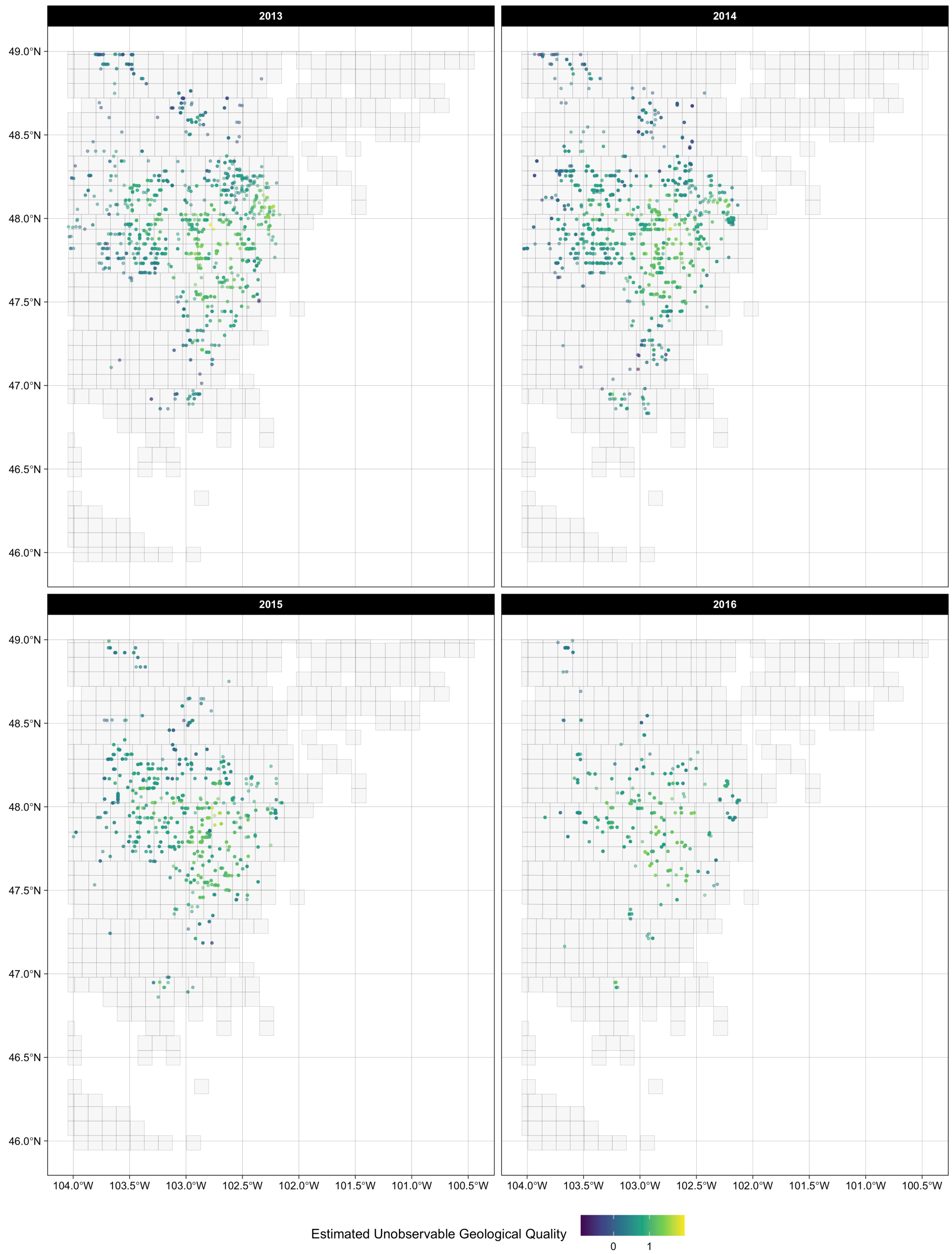

Figure A.5: Spatial Distribution of the Estimated Geological Characteristic by Year

Note: This figure illustrates the estimated geologic feature for each horizontal well completed between 2013 and 2016 by year. In this figure, each square is a section in the Public Land Survey System, whereas each dot indicates an individual well's geological characteristic. It is apparent that the share of drilling of horizontal wells with (relatively) small estimates decreased significantly starting in 2014, corresponding to the beginning of the oil price crash.

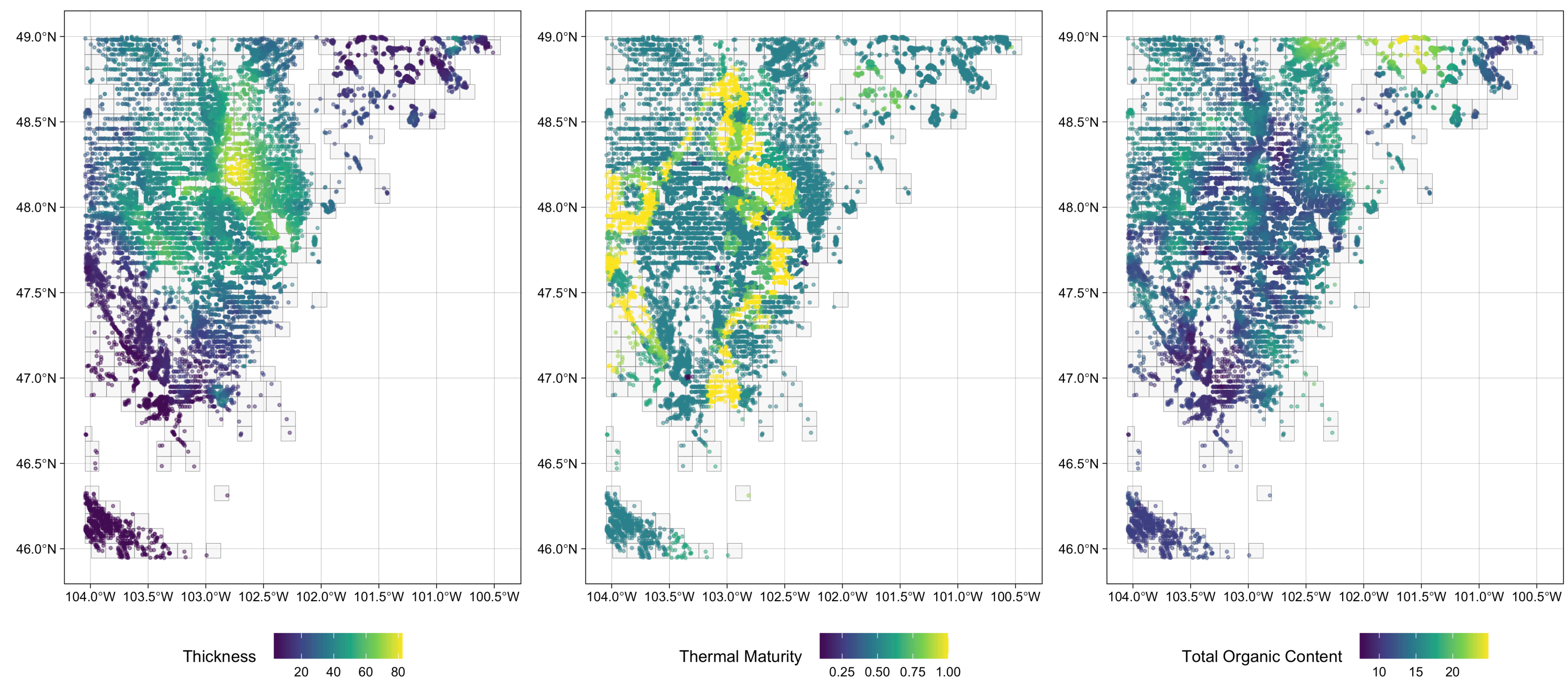

Figure A.6: Spatial Distributions of Geological Characteristics

Note: This figure depicts the spatial distributions of three geological features—thickness, thermal maturity, and total organic contents, which are available from the NDGS' geological survey data— for the horizontal wells in our sample. In this figure, each square is a section in the Public Land Survey System, whereas each dot indicates an individual well's geological characteristic.

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