Decomposing "the" Elasticity of Demand: Empirical and Policy Insights from 300 Million Natural Gas Bills

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Abstract

Public policy typically employs time- and group-invariant policies—partially due to historical limits that have prevented precise identification of the heterogeneity underlying key parameters. We consider an important market—natural gas—where these limits have been relaxed and harness 300 million residential bills to identify income- and season-specific own-price elasticities. Exploiting service-territory spatial discontinuities and household-specific exogenous time-series variation, we show this demand elasticity varies substantially across seasons, income groups, and their interaction—from 0.06 (summer) to −0.61 (winter). This heterogeneity suggests an unexplored, *implementable*, and generalizable policy avenue—shifting fixed costs of operation into summer months—that is potentially more efficient and progressive than prevailing practices.

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1 Introduction

Governments typically tend toward time-invariant taxes and policies. Similarly, economic research historically focused on estimating a single own-price elasticity of demand for a good (*e.g.* Houthakker and Taylor 1970; Becker, Grossman, and Murphy 1994; Yatchew and No 2001). However, if elasticities vary across space, time, and/or demographic groups, then this single estimate of "the" elasticity of demand is a weighted average of the true, latent, heterogeneous elasticities. To the extent that economic policies—*e.g.*, taxes—and our fundamental understanding of consumers and markets depend upon a precisely identified estimate of this elasticity, ignorance of such heterogeneity creates potential inefficiencies for policy and blind spots in our knowledge.

Of course, the literature historically focused on a single value of the elasticity of demand for good reason: researchers face constraints on numerous fronts, often weighing opportunities for credible identification with statistical power and general data availability. After conditioning on settings with plausibly exogenous variation in price, studies typically had insufficient statistical power to meaningfully consider heterogeneity.

The "Age of Big Data" offers the potential for economists to uncover this generally unobserved heterogeneity, permitting researchers to *drill down* by time, location, and group—while still maintaining sufficient statistical power—and exploit plausibly exogenous variation for identification. This ability to disaggregate estimates of demand—and its elasticity—both across heterogeneous groups of individuals (within time) *and* within the same groups over time presents a tremendous opportunity to reveal dimensions of policy inefficiency and/or inequity that were previously unobservable.

But the concept of *big data* alone is not a silver bullet, as larger datasets do not inherently solve the fundamental problem of identification. Researchers must still grapple with simultaneity, selection, and the many other forms of endogeneity.

Accordingly, this paper designs a novel identification strategy that we couple with a dataset containing 300 million residential natural-gas bills—for the fifth-largest economy in the world—to overcome the challenge of identifying casual estimates of income- and season-specific own-price elasticities of demand. We isolate plausibly exogenous variation in residential natural gas prices to identify own-price variation in two ways. First, we exploit a long-established spatial discontinuity between two major utility-service territories, with residential consumers arbitrarily residing on either side of the border (Ito 2014). Second, in order to increase variation in the price signal we use a supply-shifting instrument that exploits the two rate-of-return-earning utilities' subtly different passthrough rates that generate differing prices of natural gas on either side of the spatial border. When combined with a household-level dataset encompassing over 300 million natural gas bills, these arbitrary differences in prices reveal that consumers' price responses vary by season, by income group, and by these factors' interactions. Further, in an interesting behavioral wrinkle, we show that households do not react to their current bills. Instead, households response to bills from two billing periods prior.

Beyond providing a view of how *big data* can deepen our understanding of elasticities and their relevance, our selected case contributes to the broader body of knowledge in several ways. First, due to the emergence of frac(k)ing technology, natural-gas prices have dropped massively and regulation of this fossil fuel has risen to a first-order policy issue in the US. Second, natural-gas consumption (*i.e.*, heating behavior) varies considerably by season and income; we find substantial differences in elasticities across seasons, income groups, and their interaction, with households appearing unresponsive to prices in warm months and low-income households becoming more elastic than high-income households in cold months. Third, the natural-gas billing context presents interesting behavioral questions related to (**1**) price salience (*e.g.*, Sallee 2013; Ito 2014) and (**2**) income smoothing (*e.g.*, Stephens 2003; Mastrobuoni and Weinberg 2009; Shapiro 2005). Finally, the insights on the heterogeneity underlying "the" elasticity of demand suggest relevant, easily implementable, and empirically grounded policies (*e.g.*, Diamond and Saez 2011) that can increase the efficiency and progressivity of taxes and cost collection. Each of these specific contributions demonstrates the value of our case study and illustrates the potential broader impact of judiciously embracing the data to reshape important parameters in economics.

2 Background for the current case study

2.1 Why natural gas?

While coal dominated all other fossil fuels throughout the late 19$^{\text{th}}$ and most of the 20$^{\text{th}}$ centuries, new technologies enabling gas extraction from below the surface—hydraulic fracturing ("frac(k)ing")—is unearthing ample supplies of low-cost natural gas that will foreseeably fuel the first half of the 21st century. Potentially furthering the rise of natural gas within energy markets is the fact that fracking received significant exemptions from the Clean Air Act, the Clean Water Act, and the Safe Drinking Water Act via the Energy Policy Act of 2005 (Environmental Protection Agency 2013). Subsequently, natural gas production in the United States has expanded dramatically, and natural gas prices have fallen considerably—frequently residing at half of their pre-2005 levels (Hausman and Kellogg 2015). Further, in 2016, natural gas surpassed coal as the main source of energy for electricity generation in the United States, and half US residences use natural gas as their main heating fuel (U.S. Energy Information Administration 2016b). US residential consumers—depending on the severity of the winter—spend approximately 50–80 billion dollars per year on natural gas.[1]

The low price and abundant volumes of natural gas, coupled with natural gas's status as the cleanest and most efficient fossil fuel (Levine, Carpenter, and Thapa 2014; National Academy of Sciences 2016), have prompted broad public and policy support for using natural

1. Authors' calculations, BLS (2017) and U.S. Energy Information Administration (2016b).

gas in end uses and in the electricity generation.[2] Such support partially stems from natural gas's low carbon content per BTU, leading some to refer to natural gas as a "bridge fuel," *bridging* society toward a future powered by largely carbon-free sources of renewable energy.

However, natural gas is not without critics. The most common criticisms of current natural gas policy center on environmental degradation—including methane leakage, groundwater contamination, the possible triggering of small earthquakes, increases in air pollution, and higher incidence of accidents from the large number of trucks servicing fracking sites (Glanz 2009; Bao and Eaton 2016). More broadly, researchers have critiqued inefficient and potentially regressive pricing (and regulatory) regimes used in the consumer-facing side of the industry (Borenstein and Davis 2012; Davis and Muehlegger 2010).

Despite its policy relevance, there is a relative dearth of (well) identified estimates for the own-price elasticity of the demand for natural gas.[3] Specifically, we are unable to find any published research that pairs consumer-level data with appropriate identification strategies to causally estimate a price elasticity of demand for natural gas that carries a causal interpretation. Table 1 lists previous studies, the type of data they used, and the resulting estimates of the own-price elasticity of demand. As Table 1 shows, past papers either estimate the elasticity of demand for residential natural gas using aggregated data (*e.g.*, Hausman and Kellogg 2015; Davis and Muehlegger 2010) or using micro data with average prices (*e.g.*, Alberini, Gans, and Velez-Lopez 2011; Meier and Rehdanz 2010).[4] The majority of these papers do not attempt to deal with bias resulting from multiple sources of simultaneity, which we discuss below.

2.2 The benefits of bigger data

Research on the price elasticity of demand for natural gas faces two major challenges: insufficient data and multiple potential sources of endogeneity. Many available datasets aggregate households' consumption across both space and time. When coupled with utilities' multi-tiered volumetric pricing regimes, income-based discounts, and fixed charges, such aggregation makes it impossible for researchers to match consumers with the actual prices they face.

Compounding this challenge is the fact that research into the elasticity of demand for natural gas must also consider multiple potential sources of endogeneity. The first source of endogeneity is the classic simultaneity that stems from the fact that quantity and price

2. The fact that an increasingly large share of natural gas is produced in the United States also wins natural gas considerable political support (Levine, Carpenter, and Thapa 2014).

3. Though several previous papers have offered estimates for the price elasticity of demand for residential natural gas, the existing natural-gas demand elasticity literature addressing these issues is sparse relative to that of the electricity literature (Rehdanz 2007). A cursory Google Scholar search returns approximately 148,000 results related to *economics, elasticities, and electricity*; equivalent searches for *coal* and *gasoline* return approximately 70,000 results each. A similar search for articles related to *natural gas* finds fewer than 40,000 results. (The authors performed these searches in January 2017.)

4. The exception is Rehdanz (2007), who uses a two-period sample from West Germany, where it appears average price equalled marginal price. Rehdanz does not, however, address the endogeneity of price.

result from the equilibrium in a system of equations. Unlike the electricity sector, natural-gas customers' rates change on a monthly basis—often updating as a function of gas wholesale prices paid by the retail utilities. The second source of endogeneity results from the fact that price is mechanically a function of quantity in block-rate price regimes. As a household's consumption increases, its marginal price increases in discrete steps. Consequently, average price increases with the quantity consumed. Thus, a simple, unidentified regression of quantity on price will result in a biased—and potentially positive—estimate of the price elasticity of demand.

In order to overcome both the aggregation problem and the endogeneity issues resulting from increased block-rate pricing, this paper harnesses a dataset of approximately 300 million residential natural gas bills in California. Expanding upon Ito (2014), we exploit a spatial discontinuity between the service boundaries of two large natural-gas utilities. Given the scale of our data, we resolve the cross-border differences in monthly prices of residential natural gas resulting from the utilities' differing passthrough of upstream natural gas prices, and subsequently, we are able to identify natural gas elasticity as observed in consumers resulting behaviors.[5] This empirical strategy ensures that identification comes from (i) comparing neighboring households, and (ii) isolating the exact and exogenous source of the difference in natural-gas prices across this border (*i.e.*, differences generated by the utilities' regulated passthrough of upstream prices). Further, we use variation in day-of-month on which households' bills begin to generate additional plausibly exogenous variation in prices *at the household level* within a given month-of-sample and utility. The implication of this approach—and consequently the benefits of the large dataset—is that we are able to causally identify the elasticity of demand for residential natural gas.

2.3 Contributions of the case

This paper is the first to address the aggregation and endogeneity issues impacting natural gas elasticities. Furthermore, the paper makes four concrete contributions to the literature on estimating price elasticities of demand.

First, the natural gas market in this paper provides a unique setting as natural-gas utilities update their prices each month using formulaic passthrough of wholesale prices to consumers.[6] To overcome potential endogeneity, we combine a spatial discontinuity with a *supply-shifting* instrumental-variables (IV) approach. We instrument the utilities' consumer-facing prices with the weekly average spot price of natural gas at a major natural gas distribution hub in Louisiana (the *Henry Hub*). This instrument is valid, as we know the formula

5. Ito (2014) utilizes a similar, cross-border empirical strategy to identify the own-price elasticity of demand for residential electricity, but in California's electricity setting, there are many price tiers—and some remain fixed while others move. In our natural-gas setting, we only have two tiers that often move together. Thus, we use a different source of cross-border variation: the utilities' differential passthrough of/response to upstream natural-gas prices.

6. Electricity markets generally update cost passthrough with less frequency and with lower variance.

of how utilities passthrough the price (providing a strong first stage), and the price is determined prior to within-bill consumption (strengthening the exclusion restriction). Jointly, the spatial discontinuity and spot-price instrument isolate plausibly exogenous variation in residential natural gas prices between neighboring households due to the two utilities' differential passthrough of spot-market prices—and due to households' arbitrarily different billing-period start dates. In other words, in this multi-part empirical strategy,[7] the identifying variation in a household's price of natural gas comes from (**1**) on which side of a long-established border[8] the household sits, (**2**) the subtly different pricing rules and buying strategies governing the two rate-of-return-earning utilities as they individually respond to and passthrough prices in the upstream spot market for natural gas, and (**3**) on which day of the month a household's bill begins. Jointly, this strategy helps us to cleanly identify households' consumption responses to variation in the price of residential natural gas, pooling across households.

Our second contribution builds upon the fact that we observe whether households are part of a low-income program that provides subsidized natural gas to households. We use this knowledge to estimate price elasticities by high- versus low-income households, a novel outcome enabled by our approach and rich data.

Third, we observe billing at a roughly monthly frequency for the households in our sample, allowing us to estimate seasonal elasticities as well as price elasticities specific to income-group by season. We show that decomposing a traditionally pooled elasticity provides interesting insights and potential policy improvements.

Finally, due both to the temporal resolution of dataset and to the fact that we observe households over long periods of time in the same housing structure, we determine whether households respond to current or lagged prices. This result bears evidence on the salience of natural gas bills.

While we find that on average, the price elasticity of demand for residential natural gas ranges from −0.23 to −0.17—in keeping with expectations for this elasticity—we notably find evidence of heterogeneity in this elasticity along the dimensions of season and income: Both lower-income and higher-income households are essentially inelastic to price in summer months; however, in winter months, lower-income households are substantially more elastic to price than higher-income households. Such nuance in our results reveals unexplored policies with the potential to increase both efficiency and progressivity in settings where externalities from natural gas consumption are priced. Additionally, we show evidence that households respond to lagged electricity prices—a result consistent with rational inattention following from the difficulties households face in finding real-time information on natural gas consumption and prices. In addition to motivating previously unexplored policies with the potential to enhance efficiency and reduce the burden on the poor, these heterogeneity findings also supply insights into other *pooled* elasticity estimates that do not consider underlying

7. Coupled with the rich set of fixed effects that our dataset allows.
8. Between underground, utility-owned natural gas networks.

heterogeneity. We discuss these case-specific findings in the following sections and expand on their implications in our conclusions.

3 Institutional setting

To motivate our strategy for causally estimating the price elasticity of natural gas demand, we will first explain the institutional and physical setup of the natural gas industry in the United States. This market is commonly divided into four segments: (1) production and processing, (2) transportation, (3) storage, and (4) local distribution companies (LDCs). Figure 1 illustrates the basic institutional organization of the natural gas industry.[9] The four segments we discuss below roughly follow Figure 1 except that they exclude end users (those users who only consume natural gas) and the liquid natural gas import/export-based segments of the market. While this paper focuses on the behavior of residential natural gas consumers, part of our identification strategy relies upon a basic understanding of the wider industry—specifically in understanding which instruments may shift supply without affecting demand. After discussing these four segments, we then describe the multi-tier pricing structure employed by the two Californian natural gas utilities discussed in this paper.

3.1 Market segments

Production and processing Natural gas enters the market at the wellhead, where it is produced and first sold (Brown and Yücel 1993). Some wells produce only natural gas, while other wells produce natural gas in addition to crude oil (Levine, Carpenter, and Thapa 2014). The raw product then moves from wellheads to processors. Processors remove impurities and separate the raw product into multiple commodities[10] (Levine, Carpenter, and Thapa 2014).

Transportation High-pressure pipelines transport processed natural gas from production and processing areas to both intermediate users (storage facilities, processors, LDCs) and final users (electricity generators, industrial users, commercial users, and residential users).[11] Extensive spot markets and futures markets sit at the major hubs along this pipeline. Notably, Louisiana's Henry Hub connects to 13 intrastate and interstate pipelines. The Henry Hub is the designated delivery point for the New York Mercantile Exchange's natural gas futures contracts, and the Henry Hub price is generally regarded as a nationally relevant price (Levine,

9. We include liquid natural gas (LNG) in the figure for completeness, but liquid natural gas does not play a large role in the natural gas market in the United States: LNG imports currently account for less than one percent of natural gas imports and accounted for three percent of imports at their peak in 2007 (Levine, Carpenter, and Thapa 2014). For this reason, we omit LNG for the rest of this paper.

10. Separating "natural gas" from "natural gas liquids".

11. Figure A1 maps this pipeline network for the continental United States. Private companies own and operate segments of the pipeline; these pipeline companies' rates are regulated at the state level and the national level (Levine, Carpenter, and Thapa 2014).

Carpenter, and Thapa 2014).[12] Figure 2 depicts the Henry Hub spot price from 1997 through 2016. In general, transportation costs represent a substantial percentage of natural gas prices.[13] Thus, the natural gas transportation network creates a nationally integrated market and simultaneously contributes to a sizable portion of the prices paid by natural gas end users.

Storage Storage plays a major role in several parts of the natural gas market, but all parties store mainly for the same reason: volatility within the market. Due to its major roles in heating and electricity production, natural gas demand is strongly driven by weather and can be unpredictable in the short run. To combat price volatility and to be able to meet peak demand, both local distribution companies and large natural gas consumers store gas underground (Levine, Carpenter, and Thapa 2014). Producers utilize storage to smooth production.

Local distribution companies Local distribution companies' primarily distribute natural gas to their contracted end users—industrial, residential, and commercial consumers of natural gas. To accomplish this task, LDCs purchase natural gas through both spot markets and longer-term contracts. In addition, LDCs own and operate their own pipeline and storage networks. To cover the fixed costs involved in their pipelines, storage, and administration, LDCs often utilize a combination of two-part tariffs and multi-tiered pricing regimes—though some utilities fold all of their costs into their volumetric pricing. State utility commissions (*e.g.*, the California Public Utilities Commission) regulate LDCs' price regimes, allowing the LDCs to earn a regulated rate of return (Brown and Yücel 1993; Davis and Muehlegger 2010; Levine, Carpenter, and Thapa 2014).

3.2 Natural gas pricing in California

The California Public Utilities Commission (CPUC) regulates the two utilities from which we draw data in this paper: Pacific Gas and Electric Company (PG&E) and Southern California Gas Company (SoCalGas). Because we analyze residential natural gas consumers' responses to natural-gas retail prices, the most relevant regulations facing PG&E and SoCalGas are CPUC's price and quantity regulations. In addition, the California Energy Commission (CEC) defines geographic climate zones (see Figure A3), which, in part, determine households' price schedules (California Energy Commission 2015, 2017).

12. Part of our identification strategy hinges upon the fact that the utilities in this paper purchase natural gas within this spot market.

13. According to Levine, Carpenter, and Thapa, in 2011–2012, 72 percent of consumers' average heating costs originated in "transmission and distribution charges". Levine, Carpenter, and Thapa also note that in 2007–2008 "transmission and distribution charges" accounted for 41 percent of consumers' average heating costs. It is worth keeping in mind that consumers' average heating costs fell approximately 20 percent in this period.

For households served by PG&E or SoCalGas, a bill depends upon five elements:[14]

1. The **two-tiered price schedule** set by the utility
2. The **total volume of natural gas consumed** during the billing period
3. The **season** (*summer* or *winter*) in which the bill occurs
4. The **climate zone** into which the household's physical location falls
5. The household's **CARE (California Alternate Rates for Energy) status**[15]

Figure A4 provides an example of a typical residential natural gas bill from PG&E.

Both PG&E and SoCalGas utilize two-tiered pricing regimes. The California Energy Commission divides California into 16 climate zones in which households' needs for heating should be relatively homogeneous (California Energy Commission 2015, 2017; Pacific Gas and Electric Company 2016). The utilities also divide the year into heating (winter) and non-heating (summer) seasons. Based upon a household's climate zone (determined by the household's location) and the season, the CPUC determines a volume of natural gas that should be adequate for heating during the course of one day. This volume of natural gas is called the household's *daily allowance*. Multiplying the household's *daily allowance* by the number of days in the billing period gives the household's *total allowance* for the bill. For each unit (*therm*[16]) of natural gas up to the bill's *total allowance*, the household pays the first tier's per-unit price (*baseline price*). For each unit of gas above the household's *total allowance*, the household pays the second tier's per-unit price (*excess price*). Figure 3a illustrates an example of the two-tier block-pricing regime used by PG&E and SoCalGas. Figure 3b depicts how residential consumers' (daily) tier-one allowances vary through time within a given climate zone (PG&E's climate zone *R* and SoCalGas's climate zone *1*). Figure A3 depicts California's 16 California Energy Commission (CEC) defined climate zones.

Each month, the utilities update their price schedules. The absolute difference between the first-tier price and the second-tier price also varies but tends to remain constant for several months.[17] These monthly price changes allow the utilities to charge customers at rates that reflect the prevailing price of natural gas. In fact, the utilities tie their price updates to their costs—thus linking residential rates to spot market prices.[18] If the utilities wish to change

14. Consumers' billing periods do not perfectly align with calendar months. However, PG&E's and SoCalGas's price changes do align with calendar months (during the years that our data cover). The two utilities deal with this misalignment of billing periods and price regimes slightly differently. PG&E calculates individual bills for each calendar month under the assumption that consumption is constant throughout the billing period. SoCalGas calculates a single bill using time-weighted average prices (averaging across the different price regimes). These methods are equivalent under a single linear price but differ under the actual multi-tiered price regimes. Please see the *Calculating bills* section in the appendix for more detail.

15. The previously mentioned program that provides subsidized energy rates to low-income households in California.

16. The utilities in this paper work in units of volume called *therms*. One therm is equal to 100,000 Btu (U.S. Energy Information Administration 2016c).

17. The utilities differ in the frequencies at which which they change this absolute difference: PG&E adjusts the distance between the two tiers' price much more frequently than SoCalGas.

18. The utilities report their *weighted average costs of gas* to the CPUC.

the way in which their prices are tied to market prices and other costs, they must receive authorization following a review process with CPUC. Figure 5a illustrates these monthly price-regime changes and the fairly fixed step between the two tiers. Figure 5b depicts the correlation between the utilities' baseline (first-tier) prices and the spot market price of natural gas at the Henry Hub.

A household's participation in the CARE (California Alternate Rates for Energy) program also affects the prices that the household faces. Households qualify for CARE by either meeting low-income qualifications or receiving benefits from one of several state or federal assistance programs (*e.g.*, Medi-Cal or the National School Lunch Program) (Southern California Gas Company 2016). CARE prices are 80 percent of standard prices at both tiers. In addition to defining the household's correct pricing regime in our analysis, CARE status identifies low-income households when considering heterogeneous elasticities.

4 Data

4.1 Natural gas billing data

The billing data in this paper come from two major utilities in California: Pacific Gas and Electric Company (PG&E) and Southern California Gas Company (SoCalGas). The PG&E data cover residential natural gas bills in PG&E's territory from January 2003 through December 2014. The SoCalGas data cover residential natural gas bills from May 2010 through September 2015. Thus, the two utilities' data overlap from May 2010 through December 2014. After excluding zip codes with fewer than 50 households, PG&E's service area covers 597 5-digit zip codes, with a total of 5,888,276 households and 180,663,705 bills. After excluding zip codes with fewer than 50 households, SoCalGas's service area covers 611 5-digit zip codes, with a total of 2,526,503 households and 95,335,393 bills.

The left side of Figure 4 depicts PG&E's and SoCalGas's service areas at the 5-digit zip code level. Table 2 provides a brief summary of the billing data with regard to the numbers of bills, households, zip codes, and monetary values of the bills. Tables 2 and 3 summarize prices, quantities, and other variables of interest—pooling across all observations and also splitting the data by season or CARE status. Both tables summarize the full dataset—all zip codes across both utilities–and a subset of the data based upon all 5-digit zip codes served by both utilities. We describe this subset in detail below in the *Empirical strategy* section.

The utilities' billing data are at the household-bill level: a single row of the dataset represents a single billing period for a given household. Table A17 describes the variables (columns) in this dataset. We follow the natural gas utilities' convention in defining a household (or customer) as the interaction between a unique utility account and a unique physical location identifier.

We also utilize historical data on pricing from the two utilities. As described above, these pricing data include (1) each utility's monthly two-tier pricing regime and (2) the daily allowance for each climate zone during each season. After joining these pricing data to the households' billing data, we are able to determine both the marginal price and average price (and average marginal price) for each bill received by each household.

4.2 Weather data

Data on daily weather observations originate from the PRISM project at Oregon State University (PRISM Climate Group 2004). We match these local, daily weather data to the household consumption data at the day by 5-digit-zip-code level. The PRISM dataset contains daily gridded maximum and minimum temperatures for the continental United States at a grid cell resolution of roughly 2.5 miles (4 km). Figure A5 maps a single day of average temperature from the PRISM data for the continental United States.

We observe these daily data for California from 1980–2015. In order to match the weather grids to zip codes, we obtained a GIS layer of zip codes from ESRI (Esri 2017), which is based on US Postal Service delivery routes for 2013. For small zip codes not identified by the shape file, we purchased the location of these zip codes from a private vendor.[19] We matched the PRISM grids to the zip code shapes and averaged the daily temperature data across multiple grids within each zip code for each day. For zip codes identified as a point, we use the daily weather observation in the grid at that point. This exercise results in a complete daily record of minimum and maximum temperatures—as well as precipitation—at the zip-code level from 1980–2015.

5 Empirical strategy

We now describe our empirical strategy to identify the price elasticity of demand for residential natural gas consumers. First, we present the basic estimating equation that motivates the paper's results. Next, we discuss the inherent challenges to identification in this setting. We then discuss potential solutions to these challenges and detail which of these solutions are feasible in this paper's specific setting. Finally, before moving to the results, we provide evidence for the validity of the instruments.

5.1 Estimating equation

The relationship at the heart of this paper's elasticity estimates is

$$\log(q_{i,t}) = \eta \log(p_{i,t}) + \lambda_{i,t} + \varepsilon_{i,t} \tag{1}$$

where i and t index household and time, q denotes quantity demanded, and p denotes price. Rather than choosing a specific type of price (*e.g.*, marginal), we present results for five

19. zip-codes.com

variants of price. These five types of price include the price that classical economic theory deems relevant—the marginal price—in addition to average price, average marginal price, baseline (first-tier) price, and *simulated* marginal price (defined and discussed below).[20] In the results section, we also discuss which lag of price is most salient to consumers (see Figure 6 for an example and a brief discussion of price lags). The term $\lambda_{i,t}$ represents household fixed effects, time-based fixed effects, and/or household-by-time fixed effects—depending on the specification. Our main specification in this paper uses household fixed effects and city by month-of-sample fixed effects (*e.g.*, Fresno in January 2010; also called city by year by month). A causally identified estimate of η yields the own-price elasticity of demand.

5.2 Challenges to identification

Two main sources of endogeneity threaten causal identification of η in equation 1.

The first challenge in identifying this own-price elasticity of demand is the potential endogeneity resulting from the simultaneous determination of price and quantity that resolves the supply and demand equilibrium—*simultaneity* (*e.g.*, Woolridge 2009). We will refer to this type of endogeneity as *classical simultaneity*. In the presence of classical simultaneity, standard ordinary least squares (OLS) fails to properly treat the endogeneity inherent in (1). As discussed above, many papers in the natural gas literature ignore this potential source of bias while estimating the price elasticity of demand—relying upon fixed effects, uncorrelated demand and supply shocks, and/or assumptions of exogenous prices. If classical simultaneity is indeed present in this setting, then the estimates in these papers will recover biased estimates for the elasticity of demand for residential natural gas.

A second challenge to identification in this paper results from our paper's specific context: the two-tiered price schedule within California's natural gas market. Put simply, in tiered pricing regimes, the marginal price is a (weakly increasing, monotonic) function of quantity. For the same reason, average price is also a function of quantity. Thus, when a household consumes more, its marginal and average prices mechanically increase. In terms of identifying the price elasticity of demand, this price variation is *bad variation*: the marginal price that a household faces is endogenous because the marginal price is correlated with unobserved demand shocks (Ito 2014). This bias is a specific form of simultaneity often called *reverse causality*.

In practice, one generally cannot sign the bias resulting from the classical simultaneity of price and quantity without making further assumptions regarding the correlation of supply and demand shocks. On the other hand, the bias resulting from marginal and average prices being a function of quantity results in upwardly biased estimates of demand *elasticities*. In extreme cases, this latter case of bias can yield estimates that suggest upward-sloping demand curves.

20. We define *average marginal price* as the quantity-weighted marginal price paid by a customer during her billing period. *Average marginal* price does not include fixed charges, while *average* price does.

Table 5 demonstrates the consequences of failing to address these challenges to identification by estimating the price elasticity of demand—η in equation 1 via ordinary least squares (OLS) using marginal price (columns 1–3) and baseline (first-tier) price (columns 4–6). We also vary the set of controls for each price. For a given price, the leftmost columns apply the simplest set of controls. The "identification strategy" presented in Table 5 makes no attempt to correct for the aforementioned potential biases outside of a fairly rich set of fixed effects—household fixed effects and city by month-of-sample fixed effects. Each regression controls for within-bill heating degree days (HDDs) during the billing period.[21] The leftmost column for each price uses a five percent sample of all bills from PG&E and SoCalGas (sampled at the five-digit zip code). The remaining columns (columns 2, 3, 4, and 5) use a border-discontinuity motivated sample in which we keep all zip codes where the zip code receives natural gas from both PG&E and SoCalGas (discussed in detail below; also see Figure 4). The leftmost and center columns for each price control for household fixed effects and month-of-sample fixed effects. The rightmost columns for each price control for city by month-of-sample fixed effects (*e.g.*, Fresno in January 2010).

The six regressions in Table 5 employ two different measures of price: (a) the household's marginal price during the relevant billing period (columns 1–3), and (b) the household's baseline (first-tier) price during the relevant billing period (columns 4–6). These two—rather related[22]—measures of price yield considerably different results, differing both quantitatively and qualitatively. The baseline price suggests an elasticity between –0.10 to 0.02, while the marginal price indicates a *positive* demand elasticity between 0.43 and 0.47. The substantial differences across estimates in Table 5 suggest at least one of the aforementioned biases are present. Specifically, the fact that the marginal-price based elasticity estimates are positive (implying upward-sloping demand curves), while the baseline-price based estimates are negative, suggests that the *price-is-a-function-of-quantity* flavor of simultaneity (reverse causality) is a first-order problem in this context. This interpretation follows from the results due to the fact that baseline prices are not a function of quantity, while marginal prices are a function of quantity.

While the baseline-price-based elasticity estimates appear to be reasonable in terms of magnitude, they are still not necessarily identified, as they still may suffer from simultaneity bias. Simply adding more observations in the flavor of the *big data* movement does not address this potential endogeneity: Column 4 of Table 5 does not appear any more plausible than columns 5 or 6, despite adding more than 7 million observations—the same can be said for column 1 *vs.* columns 2 and 3. In addition, the fact that the baseline-price-based estimates change sign and magnitude when we move from the 5% CA sample (column 4)

21. The number of heating degrees in a day is equal to the difference between the day's average temperature and 65. Days with average temperatures above 65°F receive zero heating degrees. More formally, we calculate the number of heating degrees for day t with mean temperature $\bar{T}_t$ (in °F) as $\text{HDD}_t = \mathbb{1}\left\{\bar{T}_t < 65\right\} \times \left(65 - \bar{T}_t\right)$. The HDDs variable above is thus $\text{HDDS} = \sum_t \text{HDD}_t / 1000$.

22. The correlation between marginal price and baseline price is approximately 0.79; see Table A1 for bivariate correlations of prices measures.

to the border-discontinuity motivated sample (columns 5 and 6) provides some evidence that *classical* simultaneity may be present. In this border-discontinuity-motivated sample, within-zip code price variation comes from utilities' differentially pricing natural gas over a set of potentially comparable households. However, whether the change in coefficients is due to removing endogenous variation or due to changes in the sample, the existence of simultaneity is fundamentally a statistically untestable issue, which stems from the theoretical setup of how market prices originate. Rather than assuming that the sample and/or fixed effects remedy the problem, we instead present a multi-part empirical strategy to directly resolve the challenge.

5.3 Solutions for identification

Having shown that OLS—even with fixed effects and extensive data—does not cleanly identify the own-price elasticity of demand in this setting, we now discuss several potential routes for identifying the causal effect of price on quantity in our setting. In the end, we opt for an identification strategy that interacts a spatial discontinuity with an instrumental variables approach.

5.3.1 Discontinuities

A common route toward identification in applied microeconomics involves finding relatively small geographic units that receive different treatments (here: prices) within the same time period. The assumption is that observable and unobservable characteristics and, more importantly, households' price responsiveness do not differ across the border, yet they are exposed to different price changes, allowing for econometric identification. Arbitrary administrative boundaries that determine policies' catchment areas provide a popular tool in this context, *e.g.*, Dell (2010), Chen et al. (2013), and Ito (2014).

In our context of natural gas in California, the boundary between PG&E and SoCalGas offers potentially arbitrary within-city (and within-zip code) variation in prices during a month. Specifically, the boundary between PG&E's and SoCalGas's natural gas service areas bisects eleven cities—in three clusters—in southern California: Arvin, Bakersfield, Fellows, Fresno, Del Ray, Fowler, Paso Robles, Selma, Taft, Tehachapi, and Templeton. The left panel of Figure 4 displays the two utilities' service areas throughout California (for zip codes sufficiently covered in the datasets). The right panel of Figure 4 zooms in on the eleven cities (39 zip codes) that PG&E and SoCalGas both serve. Within these eleven cities, PG&E serves all 39 zip codes, while SoCalGas serves 18 of the zip codes.

This identification strategy rests upon the assumption that households on one side of the utilities' border provide a valid control group for households on the other side of the border. Because the boundary mainly represents the extent of each utilities' underground distribution network and is unlikely to enter into households' preferences, the exogeneity of the boundary to household characteristics is likely to be valid (Ito 2014). The main threat to this identification strategy is that utilities' networks correlate with geographic or neighborhood characteristics over which individuals have preferences. However, we use household fixed effects, which absorb mean differences across households. Thus, for the border discontinuity to be invalid, households would have to sort in a way consistent with their elasticities, and the utilities' price series would have to differ significantly in their variances. Because the data contain considerable variation in prices for both utilities and because the panel contains approximately six years of monthly bills, this sort of sorting bias seems unlikely.

Figure 5b suggests the generating distributions for the utilities' prices are quite similar (the standard deviations of the price series are 0.0940 and 0.1053 for PG&E and SoCalGas, respectively). In addition, Table 4 provides some limited evidence[23] of balance across the utility border, comparing PG&E and SoCalGas households within season (summer or winter) and within income group. Within a season-income group, the utilities' customers appear to consume similar volumes of natural gas, receive similar numbers of days per bill, receive similar allowances on the first tier, and face similar numbers of heating degree days. SoCalGas customers tend to receive slightly lower bills, but the difference is less than half of one standard deviation of total bill amount. Figure A2 illustrates the relevant natural-gas and electricity service areas. Notably, the border between PG&E's *natural-gas* service area and SoCalGas's *natural-gas* service area is covered entirely by PG&E's *electricity* service area. This overlap allows for neighboring households to receive natural gas from two different utilities, while only receiving electricity from PG&E.

Ito (2014) employs a similar strategy within the context of electricity consumption. However, there is at least one significant difference between the electricity and natural gas contexts that prevents us from entirely adopting Ito's identification strategy: discontinuities within electricity utilities' seven-tier pricing regime. By law, the electricity utilities in Ito's study cannot change the prices of their first two tiers—they must recover changes in their costs by moving tiers three through seven. In addition, electricity utilities in California generally do not change consumer's prices each month—and prices do not change across all utilities at the same time. Thus, marginal prices in Ito's setting move differently depending upon a household's tier and utility. Ito argues that the residual variation—combining the spatial discontinuity with this pricing discontinuity and spatiotemporal fixed effects—is plausibly exogenous from demand shocks. However, natural gas (in California) has only two tiers and the absolute difference between the two tiers has very low variation. Consequently, we supplement this utility-border-based discontinuity with an additional strategy to overcome endogeneity.

23. Our data on households is restricted to information from natural gas bills.

5.3.2 Instrumental variables

The second element in our empirical strategy for identifying the price elasticity of demand for natural gas involves a traditional solution to classical simultaneity: supply-shifting instruments. In this context, the ideal supply-shifting instrument is (1) strongly correlated with the prices that the natural gas utilities charge their customers (the *first stage*), and (2) uncorrelated with residual shocks affecting consumers' demand (Angrist and Pischke 2009). In this paper, our instrument is based upon the Henry Hub spot price for natural gas.

Henry Hub spot price Specifically, we instrument the prices that consumers face (*e.g.*, marginal price, average price, baseline price) with the average spot price at Louisiana's Henry Hub in the week preceding the change in prices. We also interact the Henry Hub spot price with *utility* to allow the utilities to differentially pass through price changes. The Henry Hub spot price represents the nationally prevailing price for short-term natural gas contracts—the hub sits at the intersection of 13 intrastate and interstate pipelines (U.S. Energy Information Administration 2016a). This instrument mechanically satisfies the requirement of having a strong first stage, as both utilities base their prices, in part, on market prices for natural gas in the period preceding their rate changes—the utilities buy natural gas on the spot market, and the California Public Utilities Commission regulates how the utilities fold their costs into the price regimes that customers face on a monthly basis.

The exclusion restriction for this spot-price based instrument is less obvious, but several factors suggest the exclusion restriction is plausibly valid. First, we interact the spot price instrument with utility. This interaction, conditional on city by month-of-sample fixed effects, means that the identifying variation in our instruments comes from the difference in how the two utilities' incorporate monthly spot-price shocks into their pricing regimes. This formulaic (approved by CPUC) and heterogeneous pass-through is unlikely to correlate with demand shocks within a city (or zip code). Additional plausibly exogenous variation in residential prices within a given city and utility comes from the different days on which households' bills begin.[24]

Second, because the utilities must obtain approval for price changes before the new price regime begins, the spot price is temporally disconnected from the billing period. In other word, the utilities' costs (and approved prices) are based upon spot prices that precede the billing period by several weeks. Thus, shocks that affect the Henry Hub spot price are distinct in time from shocks that affect natural gas demand—our fixed effects will absorb any of these shocks, so long as they do not differ across the utilities' border within a month.[25]

In addition, we show that the most salient lag of price is likely the second lag of price, further disconnecting contemporaneous local demand shocks from market-level supply shocks

24. Our results are robust to eliminating this additional source of variation, *i.e.*, treating all households within a city-utility to the same price within a month of sample.

25. California's entire residential natural gas demand represents *at most* three percent of national natural gas consumption—limiting the individual utilities' ability to set/influence spot prices and the Henry Hub.

two months prior.[26] We also control for the number of heating degree days (HDDs) in the household's zip code during the households' billing period. Because residential consumers primarily use natural gas in heating applications, controlling for HDDs further reduces the opportunity for local demand shock to affect national prices. One final exclusion-restriction concern is that price variation in the spot market for natural gas may affect both residential natural-gas prices *and* residential electricity prices. In this scenario, we would not be able to separate the effect of an electricity price shock from a natural-gas price shock. However, Figure 7 suggests that (1) residential natural gas and electricity prices are uncorrelated in both levels and differences (across the utilities' border within a month of sample), and (2) variation in the residential price for electricity is uncorrelated with variation in the Henry Hub spot price of natural gas.[27] Therefore, we argue that the exclusion restriction is plausibly valid for our spot-price instrument.

Our identification strategy thus interacts the spatial discontinuity between PG&E's and SoCalGas's service areas with the Henry Hub spot price. Specifically, the identifying variation stems from the two utilities' divergent pass-through of the spot market price—differentially projecting variation in the the natural gas spot market across a tenably arbitrary border between the two utilities.

By employing a two-part identification strategy that interacts a spatial discontinuity with a price instrument, we avoid weaknesses inherent in either individual identification strategy. For instance, simply instrumenting residential prices with the spot-market price may not entirely purge the endogenous, *bad* variation from residential prices, as variation in the spot market likely results from both supply and demand shocks. Our identification strategy instead takes variation from the spot market and projects it across the utilities' border, treating neighboring households with prices that differ only due to which utility provides natural gas. Additionally, our identification strategy also allows repeated "treatments" across the discontinuity, as the utilities change residential natural gas prices each month. This repetition of treatment both increases power and diminishes concerns regarding sorting, as both sides of the border will be "treated" over time. Thus, we contend this two-part identification strategy is well-suited for the challenges to identification in this setting.

Put simply: The repeated border discontinuity ensures that we compare similar (neighboring) households. The spot-market pass-through instrument generates arbitrarily different prices for these neighboring households. Variation in the day-of-month on which a households bills begin provides additional plausibly exogenous variation at the household level—though our results do not depend upon this additional source of variation. Finally, the temporal separation between utilities' price changes (reflecting the upstream market) and consumers' demand decisions lends further credibility to this design's ability to separate supply shocks from demand shocks.

26. See Tables 7, A3–A7 for the second-stage results comparing consumers' responses to various lags in price.
27. This observation also draws upon Figure 5b.

Spot price IV, first stage Panel A of Table 6 provides the first-stage estimates for the two-stage least squares (2SLS) equations

$$\log(p_{i,t}) = \pi_{1a} p_{i,t}^{\text{spot}} + \pi_{1b} p_{i,t}^{\text{spot}} \times \text{SCG}_i + \pi_2 \text{HDD}_{i,t}^{\text{bill}} + \text{HH}_i + \text{City}_{i,t} + u_{i,t} \tag{2}$$

$$\log(q_{i,t}) = \eta_1 \widehat{\log(p_{i,t})} + \eta_2 \text{HDD}_{i,t}^{\text{bill}} + \text{HH}_i + \text{City}_{i,t} + v_{i,t} \tag{3}$$

where HH_i is a household fixed effect, $\text{City}_{i,t}$ is a city by month-of-sample fixed effect, SCG_i is an indicator for whether the household's retail utility is SoCalGas, and $\text{HDD}_{i,t}^{\text{bill}}$ is the number of heating degree days for household i during its billing period that began in month t.

While the utilities update their prices $p_{i,t}$ for each calendar month, households' bills often straddle two calendar months—and consequently two pricing regimes—which gives the household a time-weighted average of prices for the months its bill straddles (see Figure 6). We construct the spot-price instrument $p_{i,t}^{\text{spot}}$ to correspond to this pricing policy—calculating the weighted average of the relevant months' spot prices.[28] Consequently, the spot-price instrument $p_{i,t}^{\text{spot}}$ is not collinear with the city-by-month-of-sample fixed effects: within a given city-utility-month, there is residual variation in prices (spot and retail) due to staggered bill start dates.[29]

Figure 5b provides visual evidence of the first stage—illustrating (1) the strong link between the two utilities' prices and the Henry Hub spot price and (2) the utilities' differential responses to the spot price. Notably, SoCalGas's price series appears to track the spot-market price for natural gas more closely than PG&E's price series. Throughout the rest of the paper, we define the Henry Hub spot price as the average spot price for natural gas at the Henry Hub during the seven days preceding the utility's change in pricing.

Panel A of Table 6 displays the first-stage results for equation 2 using five different prices that may be relevant to households: marginal price, average price, average marginal price, baseline price, and simulated marginal price[30] (using the log of each price). Each price is the second lag of the contemporaneous price.[31] Table 7 and Tables A3–A7 compare consumers' varying responses to different lags of price.

Both Figure 5b and Panel A of Table 6 demonstrate that the spot-price based instruments are quite strong: the F statistics testing the joint significance of the instruments range from 369.9 to 1,333.2. This significance is unsurprising because the utilities purchase gas on the spot market and incorporate these costs directly into their price regimes. The significance

28. Weighting the months' spot prices by their temporal share of the bill. See the appendix section Calculating bills for further discussion of bills spanning multiple months.

29. We can drop the within city-utility-month variation induced by the staggered bill start dates by assigning bills the price (a) at the start of the billing period or (b) for the month in which the bill spends the majority of its time. These changes do not notably change the results. We include this variation because it better matches the actual mechanisms generating variation in the first stage.

30. *Simulated marginal price* refers to a simulated instrument for marginal price. We discuss this measure of price in the next section.

31. The current bill is lag zero, the prior bill contains the first lag of price, and the bill preceding the prior bill contains the second lag of price.

of the interaction between spot price and utility (SoCalGas) in the second row of Panel A in Table 6 confirms that the utilities differ appreciably when incorporating spot-market costs into their pricing regimes: PG&E's pricing regime appears to be much less responsive to the contemporaneous spot price than that of SoCalGas, matching the observation from Figure 5b above.[32] Though the city-by-month-of-sample fixed effect should control for most local demand shocks, bills do not perfectly match months. The within-bill HDDs variable $\text{HDD}_{i,t}^{\text{bill}}$ in equation 2 controls for any remaining weather-based demand shocks. The results in Table A10 demonstrate robustness to excluding (odd-numbered columns) or including (even-numbered columns) within-bill heating degree days, which suggests that the instrument is exogenous to local weather shocks, one of the key local-demand drivers in natural gas (Davis and Muehlegger 2010; Levine, Carpenter, and Thapa 2014; Hausman and Kellogg 2015).

While the first stage is quite strong for all specifications, the results in Panel A of Table 6 suggest the instrument is strongest—in terms of first-stage significance—for baseline price, followed by average marginal price, average price, marginal price, and finally simulated marginal price. A likely reason for this outcome is that baseline price is the least noisy price: it is the only price that is not a function of the consumer's quantity, and it does not include variation from changes in the size of the step between the two tiers' prices. By these terms, (simulated) marginal price is the noisiest, which is consistent with marginal price having the smallest first-stage F statistic of the five prices.[33]

5.3.3 Instrumented prices and simulated instruments

In the preceding sections, we discussed how we interact a spot-price–pass-through-based instrument with a spatial discontinuity in utilities' service areas to overcome bias stemming from the classic form of simultaneity—*i.e.*, quantity and price (our dependent and independent variables) result from a simultaneously determined equilibrium. We now discuss one additional level of our identification strategy that directly deals with the *price-is-a-function-of-quantity* endogeneity (reverse causality) present in multi-tiered pricing contexts.[34] We present three separate options for breaking this endogenous link between price and quantity, but, in the end, the options yield very similar results.

Option 1: Instrumented prices One method for breaking the endogenous link between a household's price and its quantity is simply to instrument the household's price with a variable that is aggregated at a unit above household. Consider the IV strategy discussed above: instrumenting a household's price with the Henry Hub spot-price interacted with utility.

32. One difference between the utilities' pricing regimes is that PG&E does not have a fixed charge, while SoCalGas does. Thus, PG&E recovers both fixed and volumetric costs through volumetric charges to its customers.

33. Although the first-stage estimates in Panel A of Table 6 have the flavor of pass-through results, one should keep in mind that equation 2 specifies a log-linear form (logged price as the response variable), which does estimate pass-through.

34. This endogeneity is present in marginal price, average price, and average marginal price—all three prices are functions of the individual household's quantity consumed.

Because this instrument only varies at the level of billing-period by utility, when we regress a household's endogenous price on this instrument (and our set of fixed effects) in the first stage, the variation captured by the predicted prices is only the variation that correlates with the spot price, which is determined weeks, if not months, before the household's consumption decision. Thus, if the spot price provides a valid instrument in the classical simultaneity context, it also provides a valid instrument for the second *price-is-a-function-of-quantity* endogeneity.

Option 2: Baseline price In a similar manner, the baseline price provides a valid instrument that breaks the *price-is-a-function-of-quantity* endogeneity. Because a household's baseline price is not a function of its quantity consumed, baseline price does not suffer from the same endogeneity. Baseline price is also strongly predictive of marginal (or average) price.[35] Thus, in application, one could either replace marginal (or average) price with baseline price *or* instrument one of the endogenous prices with baseline price. There is at least one drawback to this approach: baseline price, by definition, fails to capture the higher price that a household faces when the household exceeds its total monthly allowance.

Option 3: Simulated instrument Simulated instruments[36] provide a third option for breaking the *price-is-a-function-of-quantity* flavor of endogeneity. The simulated-instrument approach follows a methodology suggested in Ito (2014). Specifically, this approach creates an instrument (or proxy) for marginal (or average) price by plugging a lagged level of consumption into the current price regime, *i.e.*,

$$z_{i,t} = p_{i,t}\left(q_{t-k}\right) \tag{4}$$

The main idea for this instrument is using a household's consumption history to predict whether a household will face the baseline or excess price in the current period. As with any instrument, we want to accomplish this prediction in a way that is strongly predictive of the true outcome (the first stage) and that is uncorrelated with any recent shocks to the household (the exclusion restriction) (Angrist and Pischke 2009). For these reasons, we modify equation 4 slightly. First, we use the households' lagged consumption levels (from lagged bills 10 through 14 months prior) to calculate the share of lagged periods that exceed this billing period's baseline allowance, *i.e.*,

$$s_{i,t} = \frac{1}{5}\sum_{k=10}^{14} \mathbb{1}\{q_{i,t-k} > \bar{A}_{i,t}\} \tag{5}$$

35. The correlation between baseline price and marginal price is approximately 0.79; the correlation between baseline price and average price is approximately 0.94. See Table A1 for all bivariate correlations between our five measures of price.

36. Also called *policy-induced instruments*.

where $\bar{A}_{i,t}$ is household i's baseline allowance in time (bill) t. We then calculate the *simulated instrument* for marginal price, $z_{i,t}$, as

$$z_{i,t} = \mathbb{1}\{s_{i,t} \leq 0.5\} \times p_{i,t}^{\text{base}} + \mathbb{1}\{s_{i,t} > 0.5\} \times p_{i,t}^{\text{excess}} \tag{6}$$

Summarizing equations 5 and 6: this simulated instrument for marginal price predicts that a household will exceed its allowance when the majority of the household's past bills (using lagged months 10 through 14) exceed the current bill's allowance.[37]

Table A2 provides evidence that this *simulated-instrument* approach significantly predicts households' marginal prices. Specifically, Table A2 provides the estimate and standard error for β in the equation

$$p_{i,t}^{\text{mrg}} = \beta p_{i,t}^{\text{sim}} + \text{HH}_i + \text{City}_{i,t} + w_{i,t} \tag{7}$$

where $p_{i,t}^{\text{mrg}}$ is household i's marginal price in time t and $p_{i,t}^{\text{sim}}$ is our simulated instrument for household i's marginal price in time t $\left(\text{i.e., } p_{i,t}^{\text{mrg}}\right)$. The estimates for β in Table A2 confirm the strong "first stage" for this simulated instrument. Marginal price and simulated marginal price are strongly and significantly correlated—both t statistics are approximately 148. The two columns in Table A2 also provide evidence of the robustness of the simulated instrument to the choice of lags: the estimates using lags 10–14 or 11–13 are virtually indistinguishable. In addition, the bottom row of Table A1 demonstrates that this simulated instrument is strongly correlated with marginal price ($r \approx 0.85$) in addition to the other four measures of price.

Column 5 of Table 6 (Panel A) provides the first-stage results consistent with equation 2 but with the simulated instrument of marginal price substituted (proxying) for actual marginal price (and still instrumenting with spot price interacted with utility across the utilities' border).[38] The first stage is again quite strong in this specification, and the results are qualitatively similar to the results in columns 1–4 of Table 6, Panel A. Henceforth we will refer to the simulated instrument for marginal price as *simulated marginal price*.

All subsequent results apply our two-part identification strategy which exploits the utilities' differential pass-through of spot-market prices to obtain exogenous variation in residential natural gas prices across the border between the two utilities' service areas. To incorporate the three competing options discussed immediately above, we provide results consistent each the strategies: instrumenting with spot price interacted with utility, proxying with baseline price, and employing simulated marginal price (the simulated instrument/proxy for marginal price). We now turn to our main results.

37. This simulated instrument is robust to the choice of months 10 through 14. The goal is to keep the instrument in the same season as the current bill (maintaining a strong first stage), while allowing some temporal distance between the lags and the current period (the exclusion restriction: preventing short- and medium-run shocks from affecting both periods).

38. It is worth noting that, in this paper, any result using the simulated instrument will have fewer observations than other results, as the simulated instrument is greedier for data—for an observation to remain in the dataset, its 14$^{\text{th}}$ lag must also be in the dataset. Our other price measures are not as greedy.

6 Results

In this section, we discuss the estimated price elasticities, using the empirical strategies extensively discussed in the preceding section. After presenting the main results for the *pooled* elasticity (no heterogeneity), we examine whether households' price responses (*i.e.*, elasticities) vary by season and/or by income.

6.1 Pooled price elasticity of demand for natural gas

Panel B of Table 6 displays the elasticity results from the second-stage regression specified in equation 3. These results instrument log price with the Henry Hub spot price (interacted with utility), exploit the spatial discontinuity, and use the log of daily average consumption (in therms) as the outcome. The five columns each estimate the elasticity using the log of a different type of price: marginal price, average price, average marginal price, baseline price, and simulated marginal price. As discussed above, each price is the second lag of price, as opposed to the contemporaneous price. The estimates for the price elasticity of demand range from −0.17 (simulated marginal price) to −0.23 (average price).

Panel B of Table 6 indicates that the estimated elasticity is fairly robust to the type of price. Table A11 demonstrates that the estimated elasticity is also robust to the inclusion/exclusion of heating degree days and to the levels of fixed effects—ranging from city by month-of-sample fixed effects to zip-code by week-of-sample fixed effects (while still including household fixed effects). The robustness to type of price also demonstrates robustness to how we control for the *price-is-a-function-of-quantity* endogeneity discussed above. Tables A11–A15 demonstrate the robustness of the estimated elasticity to excluding within-bill heating degree days and varying the spatiotemporal fixed effects. Finally, Table A16 contains marginal-price based elasticity estimates as we incrementally extend the study-area. Beginning with the study area (*Common Zips*), we add the zip codes neighboring (bordering) the study area (*Neighbors 1*); we then add the neighbors of the neighbors (*Neighbors 2*); last, we add a third band of neighbors (*Neighbors 3*). Figure A6 illustrates these groups of neighboring zip codes. The estimated elasticity from the first group of neighbors (−0.19 (0.05) in column 2 of Table A16) is quite close to the elasticity previously discussed (−0.21, (0.07) in column 1); the elasticities that include the second and third peripheral neighbors diminish in magnitude (−0.12 and −0.09) but still differ significantly from zero.

Compared to their OLS-based counterparts in Table 5, the marginal-price based 2SLS estimates for the elasticity of demand now have opposite—and theoretically correct—signs. The magnitudes of the 2SLS estimates of the elasticity (approximately −0.20) are theoretically reasonable and within the range of previous findings. Furthermore, these estimates are plausibly identified and utilize consumers' actual prices.

As discussed above, the results discussed up to this point—*e.g.*, the results in Table 6—estimate the price elasticity of demand for residential natural gas using the second lag of the various prices. In order for a household to know the prices of its contemporaneous bill, the household would need to closely follow the approved advice letters published online by the utility or the California Public Utilities Commission. Otherwise, the household will learn about prices from past bills—hence the use of lagged prices. Because a household will not receive the bill for the previous billing period for several days into its current billing period—and because the household may not view the previous bill until it pays the bill (or its credit card bill, if the household uses automatic bill payment) weeks later—the household may not know the prices from its immediately previous bill until the current period is nearly over. For these reasons, it is plausible that the second lag of price is the most salient price to many households. Figure 6 illustrates an example of the timing for bill delivery, bill payment, and the relevant lags of prices.

Table 7 replicates the second-stage results for marginal price and average price but varies the lag/lead of price: beginning with the first lead of price, followed by contemporaneous price, the first lag of price, and finally the second lag of price. Tables A3–A7 provide further detail, varying the lead/lag of each of the five prices—ranging from the first lead of price to the third lag of price. Across the five types of measures of price, none of the first leads of price, contemporaneous prices, or first lags of price differ significantly from zero. For each type of price, both the second and third lags of price differ significantly from zero. For each price, the second-lag based elasticity slightly exceeds the third-lag based elasticity in magnitude, but the difference does not exceed the standard error. These results are consistent with households responding to two-to-three lags of price—as opposed to contemporaneous price—suggesting some degree of inattention by the household to the true price, akin to previous work on inattention and salience, *e.g.*, Chetty, Looney, and Kroft (2009), Sallee (2013), and Allcott and Taubinsky (2015).

6.2 Heterogeneity

We now examine evidence of heterogeneity in the price elasticity of demand for natural gas. The institutional setting of this paper motivates two relevant dimensions of heterogeneity—income level and season—as the CPUC and utilities already apply different price regimes to households depending upon (1) the season of year (summer *vs.* winter) and (2) the household's income level (specifically, CARE status). If heterogeneity exists, then the regressions in the preceding section *pool* across the heterogeneous effects. This pooled parameter estimate may still be relevant for policy applications—particularly for policies that cannot differentiate between seasons and/or income groups. However, because OLS weights heterogeneous treatment effects by their shares of the residual variation in the variable of interest—which is itself a function of (1) the numbers of observations in the heterogeneous groups and (2) the (residual) within-group variance in the variable of interest (Solon, Haider, and Wooldridge 2015)—one might wonder whether the pooled estimator always provides a policy-relevant estimate. In addition, in the presence of heterogeneous elasticities, policymakers can increase efficiency by integrating these (known) heterogeneities (Ramsey 1927; Boiteux 1971; Davis and Muehlegger 2010).

For income-based heterogeneity, we use a household's CARE status as a proxy for its income level.[39] As discussed above, households qualify for CARE by either meeting low-income qualifications or by receiving benefits from one of several state or federal assistance programs (*e.g.*, Medi-Cal or the National School Lunch Program) (Southern California Gas Company 2016). For seasonal heterogeneity, we split the calendar into winter months (October through March) and summer months (April through September).[40]

6.2.1 Income heterogeneity

To examine income-based heterogeneity in the price elasticity of demand for natural gas, we estimate the two-stage least squares equations 2 and 3 separately for CARE households and non-CARE households. Columns (3) and (4) of Table 8 supply the second-stage results from these regressions, providing estimates of the elasticity of demand by income level (CARE status).

The results in columns (3) and (4) of Table 8 suggest that the elasticity results in the previous section may in fact pool across heterogenous elasticities; we estimate that the price elasticity for CARE (lower-income) households is approximately twice that of non-CARE (higher-income) households. Specifically, using the marginal price, we estimate an elasticity of approximately −0.24 (0.080) for CARE (lower income) households and −0.14 (0.068) for non-CARE households. The "pooled" estimate corresponding to these results is −0.21 (0.071) (column (1) of Panel B in Table 6)—slightly higher than the midpoint between the CARE estimate and the non-CARE estimate.

6.2.2 Seasonal heterogeneity

To estimate seasonal heterogeneity in the price elasticity of demand for residential natural gas, we estimate the two-stage least squares equations 2 and 3 separately for winter months and for summer months. Columns (1) and (2) of Table 8 supply the second-stage results from these regressions, providing estimates of the elasticity of demand by season.

The results in columns (1) and (2) of Table 8 indicate a stark and significant difference between price elasticities in summer and winter months. Using marginal price, we estimate that the price elasticity of demand for natural gas in summer months is approximately 0.052

39. Because we do not have identifying variation in income level (or season), the heterogeneities that we estimate should be taken as descriptive for the given group, rather than causal effects of income level or season. In other words, while we estimate heterogeneous elasticities with respect to income level, this heterogeneity may have nothing to do with income and could instead result from some other (omitted) variable that correlates with income/CARE status, *e.g.*, the age and size of the physical home. However, identification of the sources of heterogeneity is not the goal of this paper; we aim to identify the elasticity of demand and demonstrate dimensions of heterogeneity. We leave it for future papers to identify the sources of these heterogeneities.

40. This definition reflects southern California's two seasons: warm and slightly less warm.

(0.029), which marginally differs from zero at the 10 percent level. The estimated elasticity for winter months is approximately −0.38 (0.14) and differs significantly from zero at the 1 percent level. The comparable "pooled" elasticity estimate corresponding to these results is approximately −0.21 (0.071) (column (1) of Panel B in Table 6). These results provide strong evidence that households' consumptive and price-response behaviors vary considerably by season—the winter-based elasticity is nearly twice the "pooled" elasticity.[41][42]

6.2.3 Income-by-season heterogeneity

Having shown potential heterogeneity across income groups (CARE status) and season, we now examine the evidence that income groups' heterogeneity varies by season by interacting the two heterogeneity dimensions discussion above (income and season).

To estimate seasonal-by-income heterogeneity in the own-price elasticity of demand for residential natural gas, we estimate the two-stage least squares equations 2 and 3 separately for the four potentially heterogeneous subgroups: CARE households in the summer, non-CARE households in the summer, CARE households in the winter, and non-CARE households in the winter. Table 9 displays the second-stage results from these regressions, providing estimates of the elasticity of demand by season and CARE status.

The results in Table 9 are consistent with heterogeneous elasticities that depend upon the interaction between household income (CARE status) and season. In other words, the difference between a household's winter and summer price elasticities varies by the household's income level. Specifically, the results in Table 9 indicate that both income groups are essentially inelastic to prices in summer months; we estimate a "summertime" price elasticity of 0.046 (0.035) for CARE households and 0.074 (0.032) for non-CARE households. Both elasticities are positive, but only one is significantly different from zero and small. In winter months, both sets of consumers are significantly and substantially more responsive to price, but CARE households are particularly price responsive. We estimate the "wintertime" price elasticity of demand for natural gas is −0.523 (0.142) for CARE households and −0.317 (0.150) for non-CARE households. Again, the pooled elasticity corresponding to these results is approximately −0.21 (0.071) (column (1) in Table 6), which is a bit lower than the average of these four elasticities. Overall, Table 9 demonstrates the potential for substantial and important heterogeneity underlying commonly estimated pooled elasticities.

6.3 Policy implications

The heterogeneity discussed above suggests that households are much more price sensitive during their high-consumption months—the winter. These high-consumption winter months

41. Table A8 reproduces these heterogeneity results using average price—rather than marginal price—with very similar results.

42. Because the current/relevant natural gas institutions divide the year into *winter* and *summer*—and because gas is primarily used for heating—we believe this summer/winter split is the most policy-relevant temporal disaggregation of the price elasticity of residential natural gas. We do not further disaggregate in time.

also correspond to the time of year in which consumers use natural gas in its most salient form: heating. When we break down the price elasticity across users and seasons, we show that subsidized (lower income) consumers display the largest price sensitivity during the winter (−0.52). Neither type of customer displays a substantial price response in the summer. These results suggest that, if suppliers want to pass through costs to (or tax) consumers, summertime may be best—both for efficiency and for progressivity.[43]

Figure 8 illustrates the seasonal heterogeneity point with simple linear demand that is quite inelastic in the summer and moderately elastic in the winter—consistent with our results. The top row of Figure 8 demonstrates that, in this scenario, deadweight loss is substantially larger in the winter than in the summer. The bottom row simply doubles the summer tax and halves the winter tax, resulting in a minuscule *increase* in deadweight loss for the summer and a substantial *reduction* in deadweight loss in the winter—implying a considerable overall reduction in deadweight loss.[44] Again, it is worth noting that this example also assumes (1) a first-best world (no unpriced costs to consumption) and (2) the goal of the policymaker is reducing deadweight loss, conditional on some level of taxation/cost-recovery. If, for instance, natural-gas consumption includes an unpriced social cost, then increasing summer taxes and reducing winter taxes could potentially further reduce market efficiency by exacerbating the unpriced costs. Similarly, if the policymaker wishes to use the tax to reduce consumption, then our results suggest that imposing a per-unit tax in the winter is much more efficient than the same tax in the summer.[45] However, our season-by-income results imply that the poor would bear the largest deadweight loss for such a tax.

The discussion above suggests an implementable dimension for tax and cost-recovery efficiency—season of year—that we have not seen recommended in the literature or applied in practice.

7 Discussion and conclusion

This paper combines millions of household natural gas bills with a multi-part identification strategy to provide the first micro-data based causal estimates of the own-price elasticity of demand for residential natural gas. Utilizing cross-border price variation between California's two largest natural gas utilities—resulting from the utilities' differential pass-through of spot-market price variation—we isolate plausibly exogenous variation in residential natural gas prices. We estimate an elasticity of −0.21 [−0.35, −0.07]. This estimate is robust to specification choices that include within-bill weather, several price instruments, and the

43. This point hinges critically on the assumption that external costs from natural gas combustion are properly priced. For global pollutants, this is the case in California because the natural gas sector is part of California's cap and trade system.

44. This toy example is meant to illustrate the idea. The most efficient seasonal tax adjustment—conditional on a level of tax recovery—would likely not imply exactly doubling taxes in the summer and halving taxes in the winter.

45. In terms of units of abatement per dollar of tax levied.

definition/type of price. The point estimates for the own-price elasticity range from −0.23 to −0.17 across five measures of price. Given the robustness of these findings, this paper provides tight bounds on a policy-relevant parameter key to applications ranging from estimating the welfare benefits of fracking (Hausman and Kellogg 2015) to analyzing the regressivity of two-part tariffs (Borenstein and Davis 2012). Because households respond significantly to price changes two to four months prior to the period of consumption—and following Ito (2014)—we interpret these estimated elasticities as fairly *medium-run* elasticities.[46]

As a second important finding, we estimate that the own-price elasticity of demand varies significantly across seasons and customer types. We show that households on a popular low-income program, which subsidizes households' natural gas and electricity, appear to be twice as elastic in their response to price as households who are not part of the program. We also show that the price elasticity varies greatly across seasons. If we average across types of households, the summer price elasticity is close to, and only marginally different from, zero. The winter price elasticity is −0.38—households are most responsive to natural-gas prices when they are heating. We further decompose the estimated price elasticity across users and seasons, and show that lower-income consumers display the largest price sensitivity during the winter (−0.52). Finally, based upon the heterogeneity underlying the own-price elasticity of demand, we suggest a simple and implementable policy that we have not seen in the literature or applied in practice: shifting fixed costs to inelastic periods. In the setting of natural gas, this policy idea has the potential to enhance efficiency and equity.

This fairly simple idea raises a wider question for future work: Along which other dimensions of consumer heterogeneity might we optimize current tax and cost-recovery policies? If policy is to take seasonal heterogeneity—or any other heterogeneity—into account, future work should decompose traditionally *pooled* elasticities and policy responses. This paper provides on example of how the *big data revolution* can enable empirical work with stronger credibility—narrowing in on settings with plausibly exogenous variation—while maintaining sufficient statistical power to reveal dimensions of policy inefficiency and/or inequity that were previously unobservable. Such work will provide policymakers with important parameters to improve market efficiency and enhance policy progressivity.

Expanding beyond natural gas, the findings within this paper demonstrate the limitations of current, aggregated understandings of own-price elasticities of demand. Elasticities help us understand how consumers respond to changes in prices (*e.g.*, Chetty, Looney, and Kroft 2009; Ito 2014), levy efficient and/or equitable taxes (*e.g.*, Ramsey 1927; Allcott, Lockwood, and Taubinsky 2018), determine the incidence of taxes/tariffs (*e.g.*, Harberger 1964; Mirrlees 1971; Atkinson and Stiglitz 1976), and analyze the potential for firms to exercise market power (*e.g.*, U.S. Supreme Court 1956). Furthermore, price elasticities feature prominently in many major policy questions today—ranging from the regulation of public utilities to the incidence and efficacy of climate-change targeting carbon taxes, and from questions

46. Ito (2014) also notes that the medium-run elasticity is often the most policy-relevant elasticity.

concerning an apparent abundance of monopolistic firms to trade wars. While each of these settings and studies provide insights into the mechanisms shaping economics behavior and efficient systems, as this paper demonstrates, the pooled estimates upon which the literature relies may blur out nuances that could potentially affect efficiency and/or equity of many policies.

As our world steps into the Age of Big Data, economics may benefit from reassessing established estimates that were previously limited by data/granularity. Rather than calling into question the benefits already gained from past work, this study raises caveats that future discussions will need to consider, if not address head-on. Big data provides opportunities for heightened awareness of where our blind spots lie and how such ignorance affects knowledge and policy. With careful analysis, larger datasets offer the potential to unlock new empirical insights and increase and efficiency and equity of public policies.

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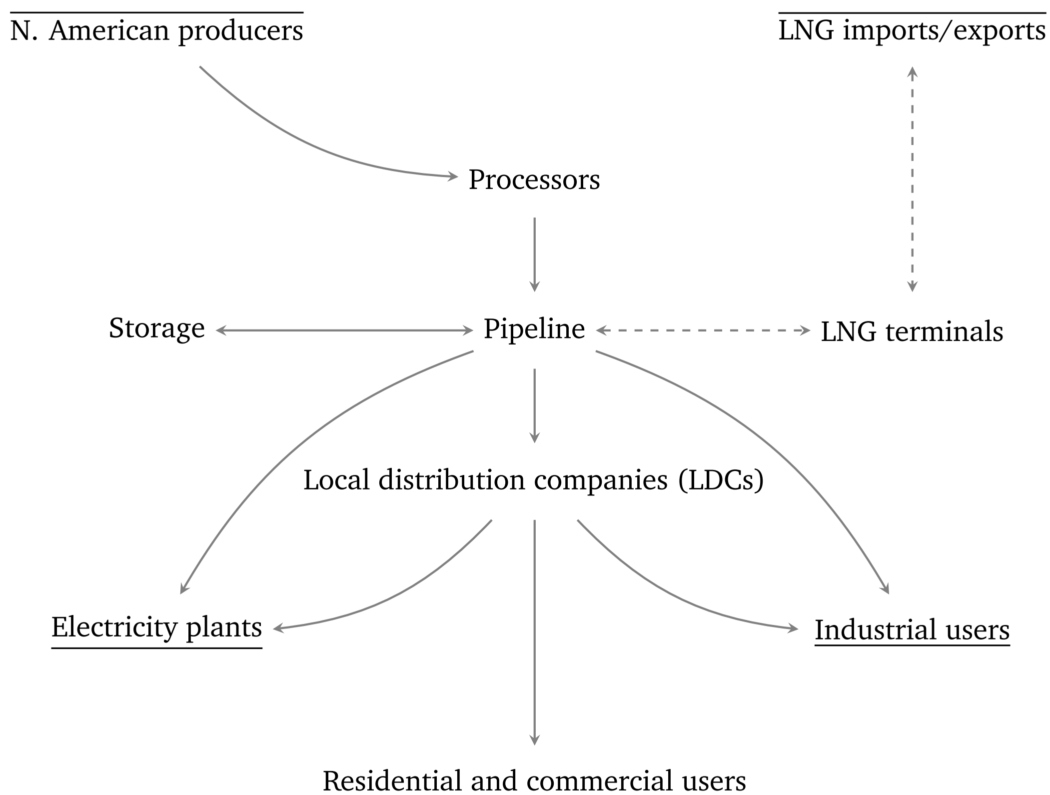
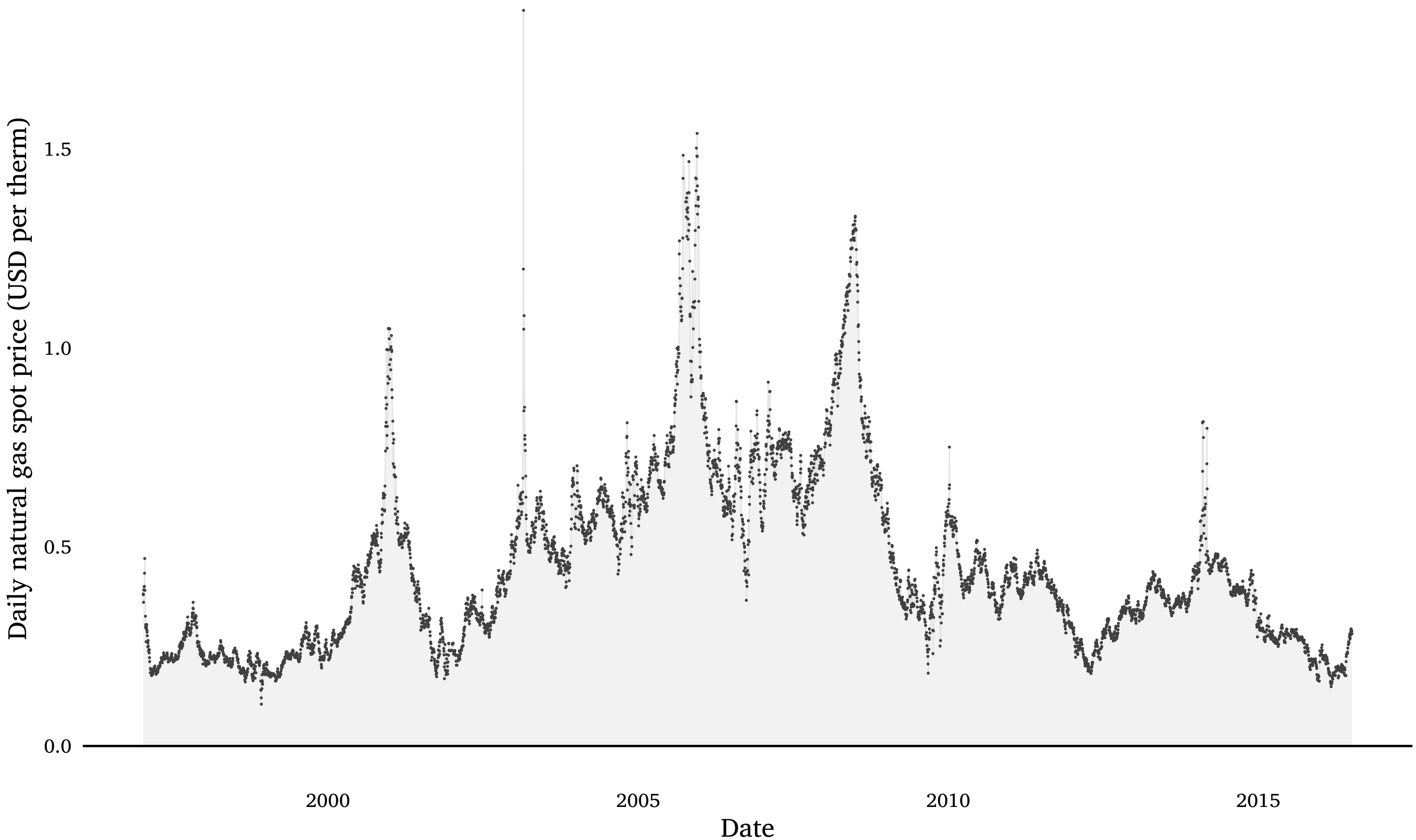
8 Figures

Figure 1: **U.S. natural gas institutional organization**



Notes: Overbars represent points of entry into the U.S. natural gas market; underbars represent end points in the market; all other labels represent intermediaries. Arrow directions correspond to the direction of the flow of natural gas. The acronym *LNG* abbreviates *liquid natural gas*. This figure is based on Levine, Carpenter, and Thapa (2014) with modification following Brown and Yücel (1993).

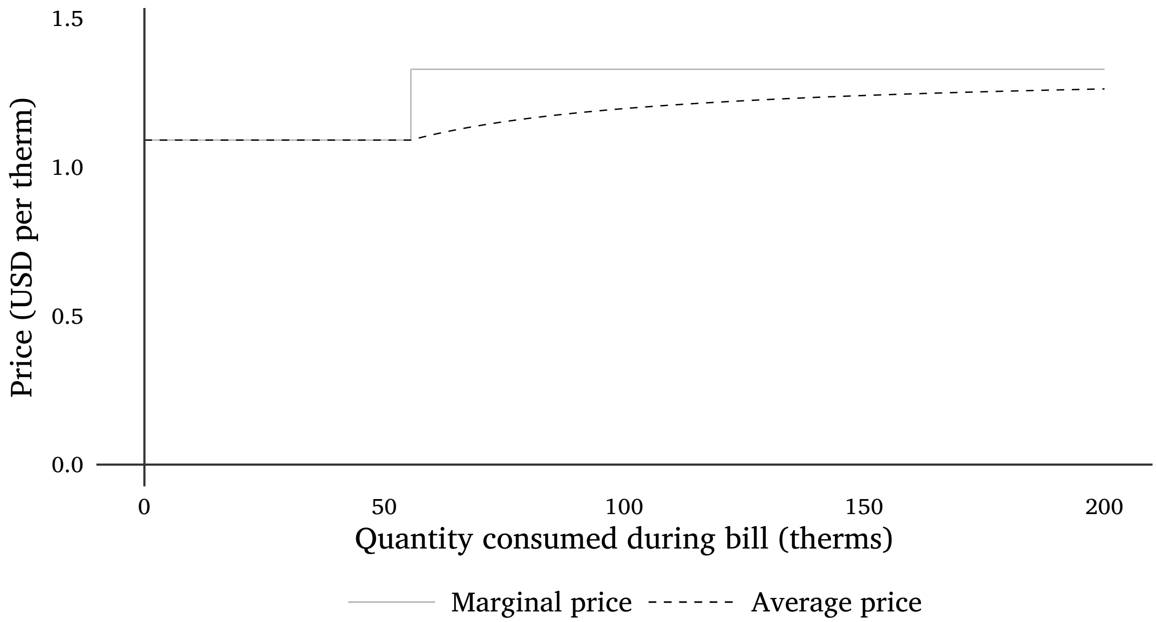
Figure 2: **Henry Hub natural gas spot price:** Daily, 1997–2016



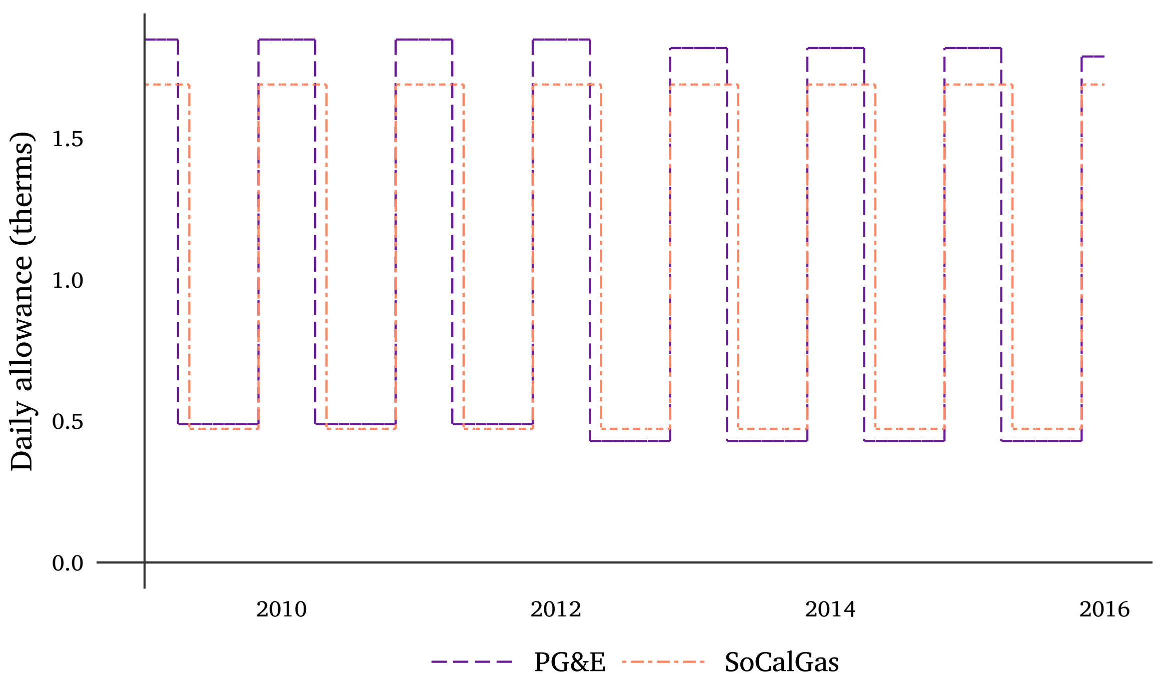
Source: U.S. Energy Information Administration

Figure 3: **Households' allowances and prices**

(a) **Allowance and marginal *vs.* average price example:** PG&E, January 2009, climate zone R

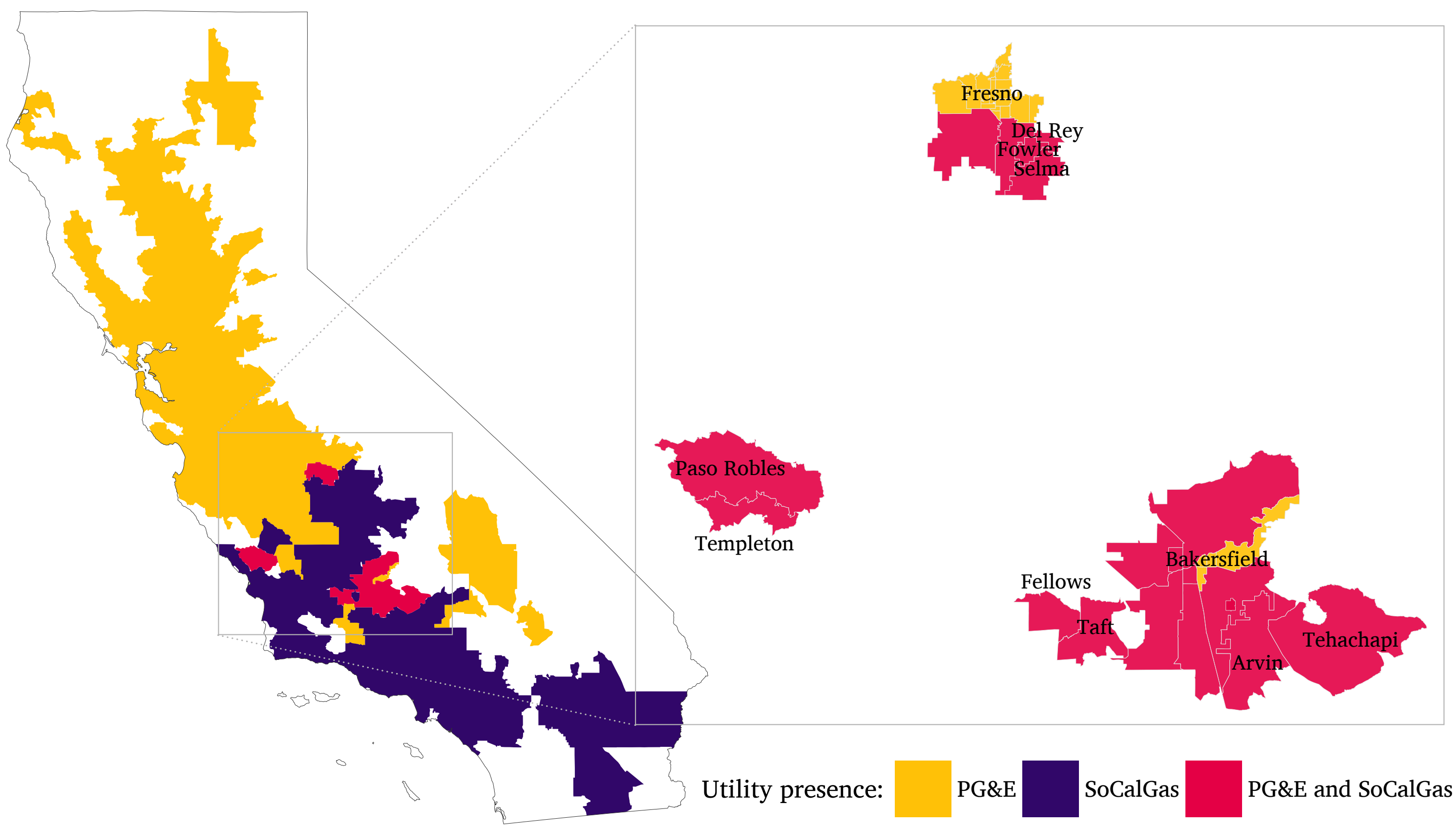


(b) **Tier-one daily allowances over time:** PG&E (zone R) and SoCalGas (zone 1), 2009–2015



Notes: Households receive daily allowances for baseline (first-tier) consumption as a function of location and season (*e.g.*, climate zone *R*, January 2009). The household pays the second-tier price on all units that exceed its allowance—comparing total consumption (during the billing period) to total allowance (daily allowance summed across the bills' days).

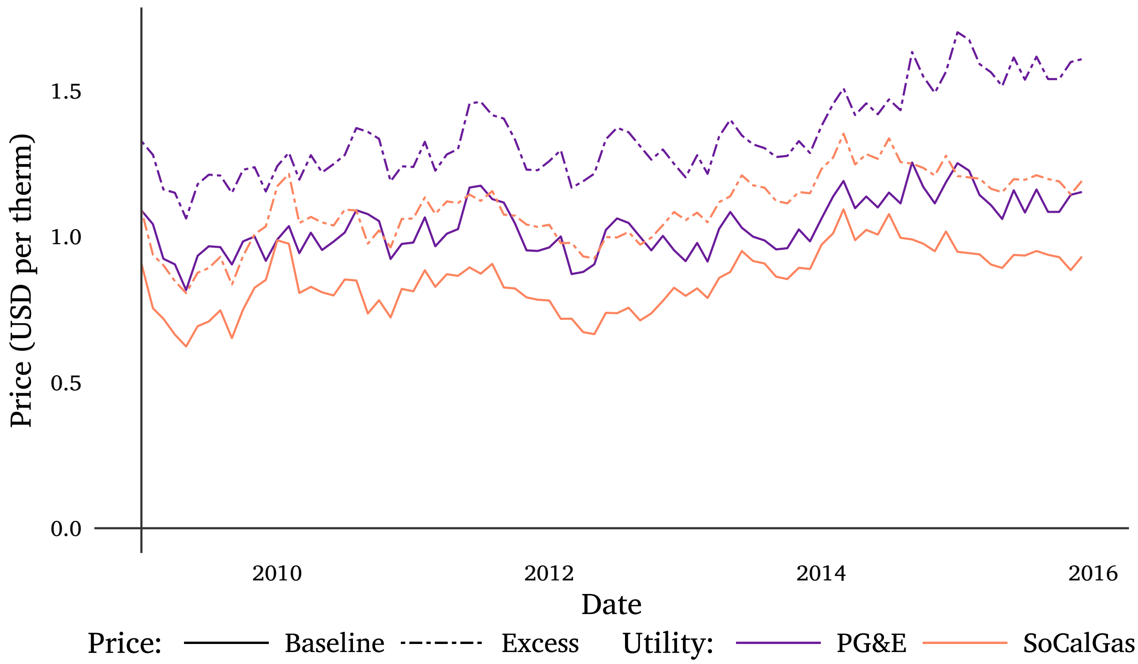
Figure 4: **Natural gas service areas and the study-area discontinuity**



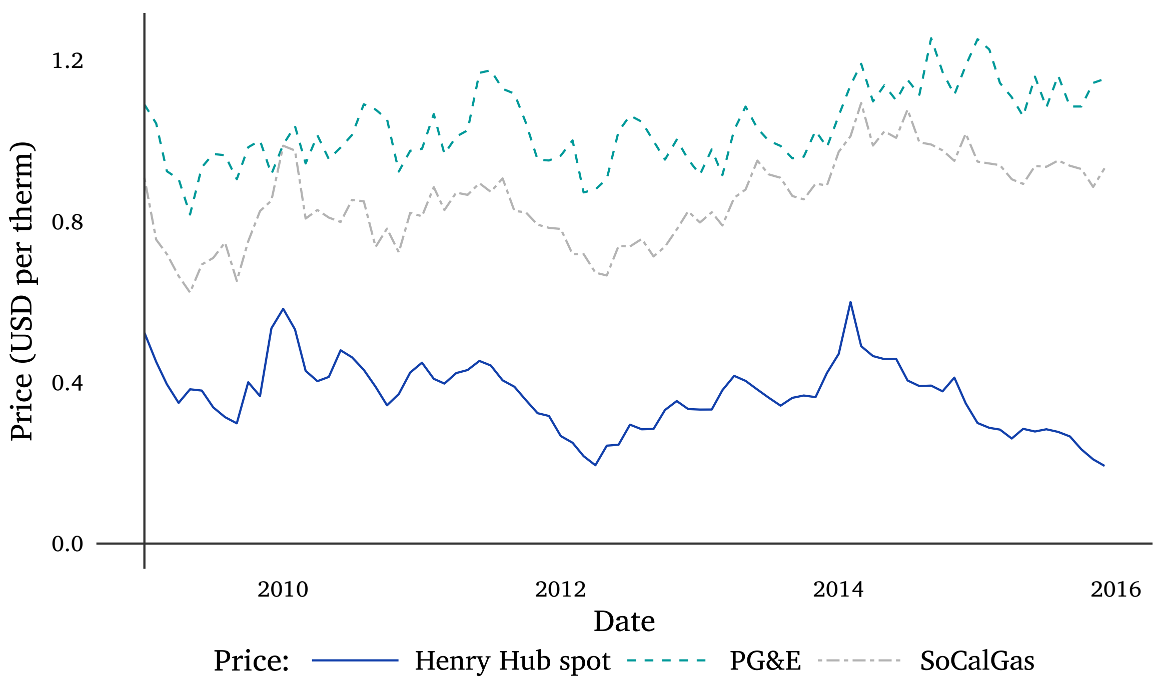
Notes: The left side of the figure displays PG&E's and SoCalGas's services areas (by 5-digit zip code). The right side of the figure zooms in on three clusters of cities that receive service from both utilities. These three clusters of cities encompass 39 zip codes; 18 of these (5-digit) zip codes receive service from both PG&E and SoCalGas. These 18 zip codes represent the main study area for the paper.

Figure 5: **Prices across utilities, tiers, and in the spot market**, 2009–2015

(a) **Price regimes over time:** PG&E and SoCalGas, 2009–2015

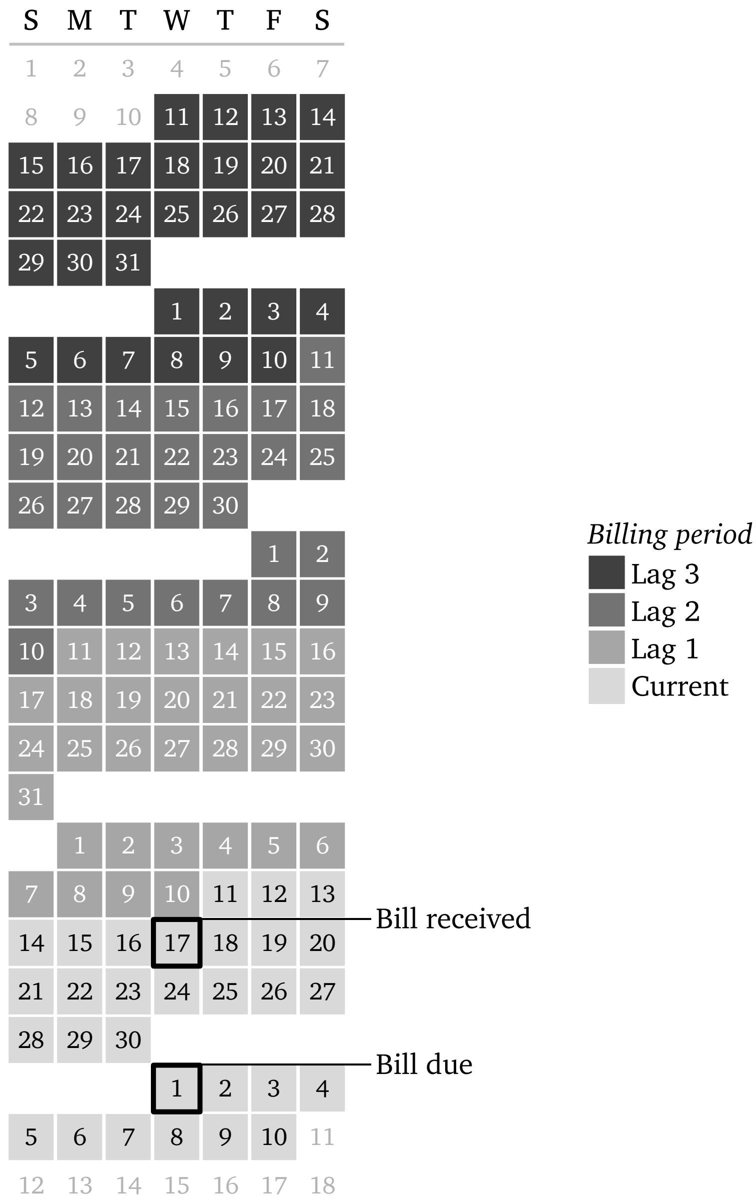


(b) **Correlation across prices** Three relevant natural gas price series, 2009–2015



Notes: *Baseline* refers to first-tier price, *i.e.*, the price a household pays for its first therm of natural gas. *Excess* refers to the second-tier price, *i.e.*, the price a household pays for each therm that exceeds its first-tier allowance (see Figure 3). The Henry Hub spot price is generally recognized as a national benchmark (U.S. Energy Information Administration 2016a; Levine, Carpenter, and Thapa 2014).

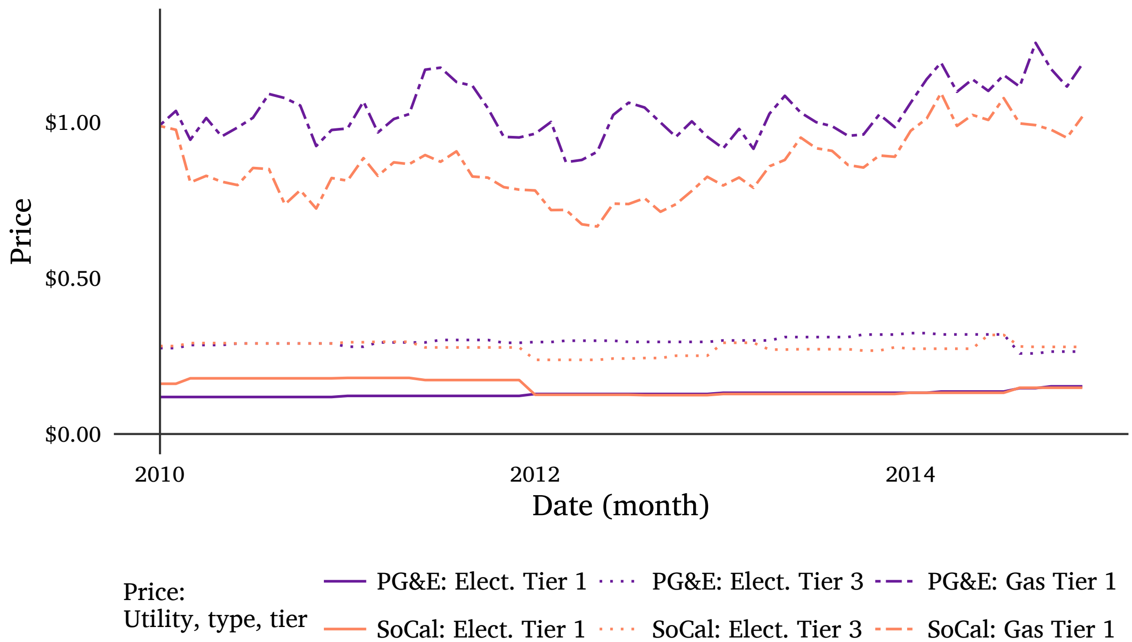
Figure 6: **Calendar months and billing periods:** Four 30-day bills and five months



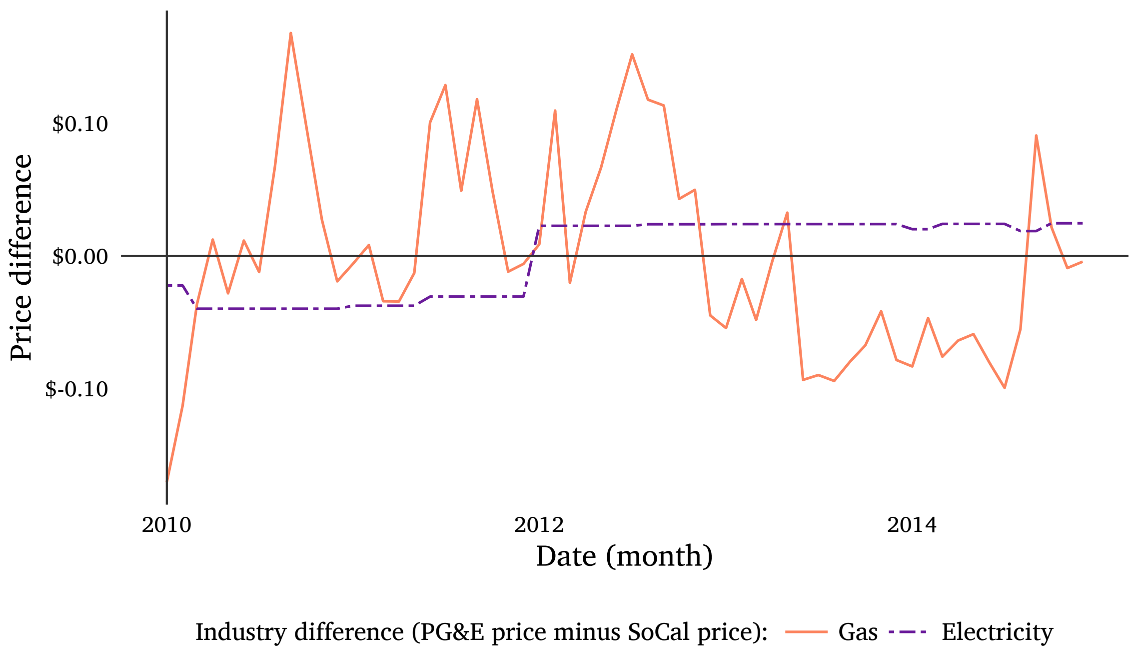
Notes: The household receives its bill from the *Lag 1* period on the fifth business day of its *current billing period* (the 17th). Payment for the *Lag 1* bill is due two weeks later (on the 1st). Now consider the question "Which lag of price is relevant?" **Current:** For the household to know the price structure for its current billing period, it must pay attention to the approval status of its utility's advice-letters correspondence with the CPUC. **Lag 1:** Again, unless the household pays attention to the utility's CPUC-approved advice letters, it will not know the prices in the *Lag 1* billing period until it receives and opens the bill. The bill arrives several days into the new period, and if the household does not see the bill until payment, it may not learn about the prices of the *Lag 1* bill until the current billing period is nearly complete. Autopay may extend this moment of salience even further into the future. **Lag 2:** Throughout the entirety of the *Current* billing period, the household will know the prices from its *Lag 2* bill, and for a non-zero amount of time, the *Lag 2* bill is likely to be the most recent set of prices the household knows. **Lag 3:** Same level of knowledge as *Lag 2* but less recent.

Figure 7: **Natural gas and electricity prices:** Comparing utilities and industries

(a) **Comparing trends in levels**, 2010–2014

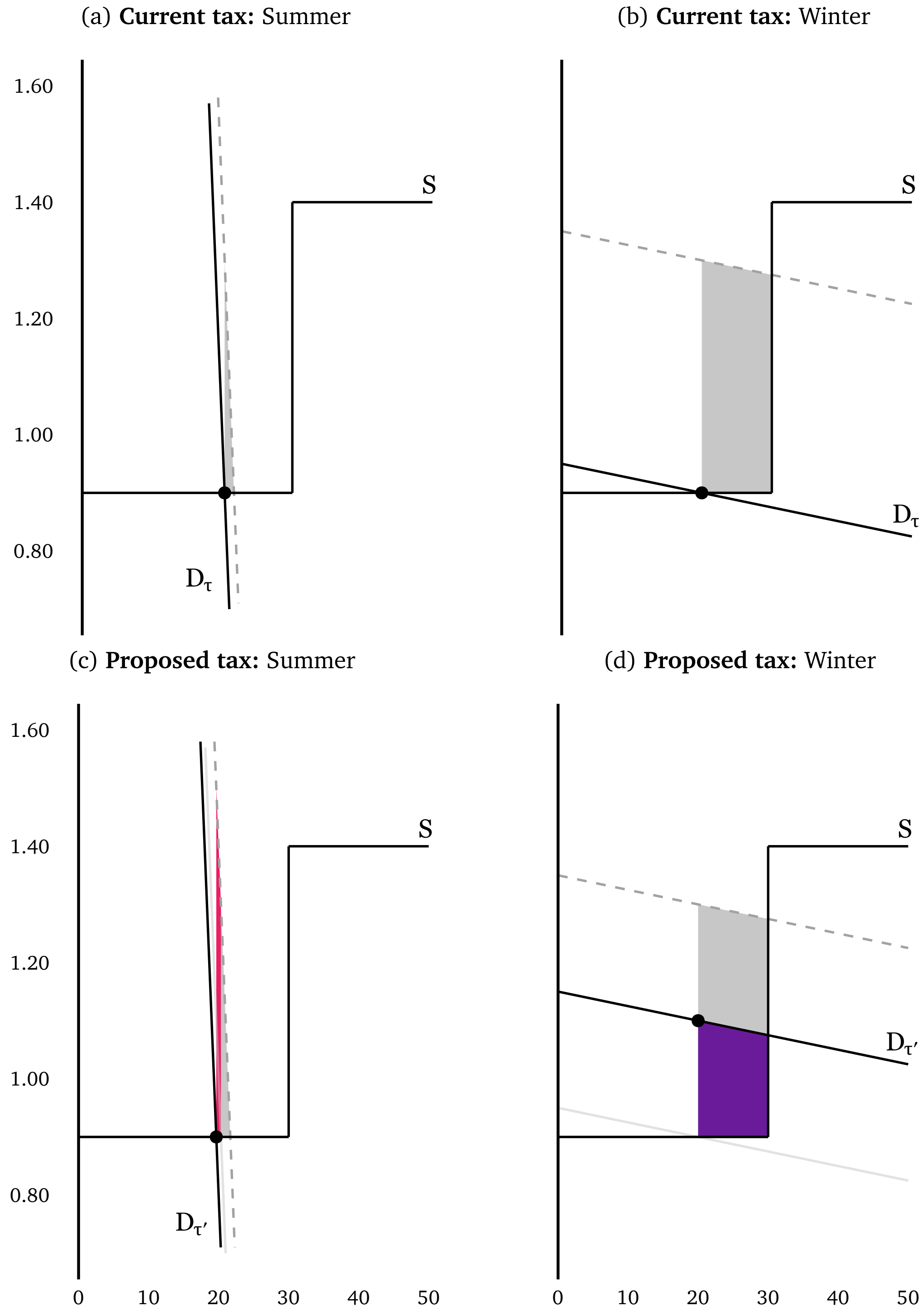


(b) **Comparing trends in differences** across utilities, 2010–2014



Notes: For the consumers in this paper, natural gas prices do not significantly correlate with electricity prices—neither in levels (Panel A), nor in differences (Panel B). *Differences* constitute PG&E minus SoCal within the same calendar month. We demean the time series of differences for each industry (natural gas and electricity). *SoCal* denotes the *Southern California Gas Company* for natural gas and *Southern California Edison* for electricity. The underlying data come from publicly available CPUC letters for the relevant utilities.

Figure 8: **Increasing tax efficiency** using seasonal heterogeneity



Notes: Each figure presents the combination of a tax (current *vs.* proposed) and a season; the *x* and *y* axes are quantity and price, respectively. The top row illustrates the two seasons under the **current tax**, where households pay the same tax per therm in both seasons. The shaded gray area gives the deadweight loss (DWL) under this tax. **Proposed tax:** The bottom row doubles the tax in the summer—increasing DWL by the narrow pink region—and halves the tax in the winter—reducing DWL by the purple region. Overall DWL decreases.

9 Tables

Table 1: **Prior point estimates:** The price elasticity of demand for residential natural gas

Paper	**Data**	**Estimate**
Davis and Muehlegger (2010)	US state panel	−0.278
Maddala et al. (1997)	US state panel	−0.09 to −0.18
Garcia-Cerrutti (2000)	Calif. county panel	−0.11
Hausman and Kellogg (2015)	US state panel	−0.11
Herbert and Kreil (1989)	Monthly time series	−0.36
Houthakker and Taylor (1970)	Time series	−0.15
Metcalf and Hassett (1997)	RECS HH panel	−0.08 to −0.71
Meier and Rehdanz (2010)	UK HH panel	−0.34 to −0.56
Rehdanz (2007)	Germany HH panel	−0.44 to −0.63

Sources: Authors and Alberini, Gans, and Velez-Lopez (2011)

Table 2: **Billing data summaries**

	Full dataset		**Border-area dataset**	
	PG&E	**SoCalGas**	**PG&E**	**SoCalGas**
N. 5-digit zip codes	597	611	18	18
N. unique households	5,888,276	2,526,503	152,418	68,407
N. bills	180,663,705	95,335,393	3,401,947	2,352,141
Approx. value (USD)	$5.71B	$3.28B	$120M	$70.5M

Notes: *Full dataset* refers to all of the PG&E and SoCalGas bills in the data. *Border-area (discontinuity) dataset* refers to the subset of the *full dataset* for households located in the 18 5-digit zip codes served by both utilities during 2010–2014.

Table 3: **Numerical summaries:** Prices, quantities, and other variables of interest

	5% Sample of California			**Border-discontinuity sample**				
		Split by utility			**Split by season**		**Split by CARE**	
Variable	**Overall**	PG&E	SoCalGas	**Overall**	Winter	Summer	CARE	Non-Care
Baseline price	0.8901	0.9823	0.7432	0.9026	0.8836	0.9204	0.8080	0.9811
	[0.1686]	[0.1206]	[0.1242]	[0.1419]	[0.1361]	[0.1448]	[0.0854]	[0.1311]
Average price	1.0138	1.1053	0.8680	1.0211	1.0008	1.0402	0.9086	1.1147
	[0.1845]	[0.1439]	[0.1439]	[0.1621]	[0.1583]	[0.1633]	[0.1004]	[0.1430]
Marginal price	1.0206	1.1277	0.8500	1.0387	1.0121	1.0637	0.9338	1.1259
	[0.2260]	[0.186]	[0.173]	[0.1983]	[0.1905]	[0.2021]	[0.1448]	[0.1944]
Therms	35.4626	37.7541	31.8135	33.8273	50.9544	17.7311	33.1136	34.4204
	[33.7995]	[36.0107]	[29.5791]	[30.7697]	[35.2487]	[11.5803]	[28.7629]	[32.3306]
Days	30.3992	30.4282	30.3530	30.3994	30.5876	30.2225	30.4040	30.3955
	[1.4275]	[1.2667]	[1.6505]	[1.3038]	[1.3843]	[1.1966]	[1.2761]	[1.3263]
Therms per day	1.1592	1.2355	1.0378	1.1063	1.6588	0.5871	1.0840	1.1249
	[1.0921]	[1.1698]	[0.9426]	[0.9936]	[1.1354]	[0.3838]	[0.9304]	[1.0429]
Total bill	36.8703	42.3938	28.0747	34.9508	52.0750	18.8573	30.3135	38.8040
	[39.5758]	[44.0564]	[29.0445]	[33.8812]	[39.8973]	[14.0069]	[27.2567]	[38.1017]
(Percent) CARE	27.43%	26.35%	29.15%	45.38%	45.00%	45.74%	100%	0%

Notes: Unbracketed values provide the variables' means; bracketed values denote the variables' standard deviations. The *5% sample of California* is based upon 5% of PG&E's and SoCalGas's natural gas bills from 2010–2014, sampling at the 5-digit zip code. The *border-discontinuity sample* represents all bills from PG&E and SoCalGas for the 18 5-digit zip codes served by both utilities from 2010–2014.

Table 4: **Balance on observables:** Comparing utilities' customers across the discontinuity

	Non-CARE			CARE		
Variable	PG&E	SoCalGas	**Diff.**	PG&E	SoCalGas	**Diff.**
Panel A: Summer						
Therms consumed	17.61	17.29	0.32	19.35	18.00	1.34
	[10.8]	[11.7]	[11.3]	[11.3]	[11.3]	[11.3]
Days in bill	30.31	29.97	0.34	30.29	29.96	0.33
	[1.16]	[1.36]	[1.28]	[1.16]	[1.36]	[1.22]
Allowance	14.17	17.22	−3.05	14.14	17.11	−2.96
	[0.805]	[8.05]	[6.14]	[0.851]	[8.17]	[4.33]
Total bill	21.58	16.45	5.14	19.03	13.52	5.51
	[14.8]	[12.4]	[13.8]	[12.4]	[9.35]	[11.9]
HDDs	0.16	0.25	−0.08	0.14	0.26	−0.12
(thousands)	[0.309]	[0.407]	[0.367]	[0.267]	[0.418]	[0.315]
N	810,949	961,824	1,772,773	973,063	320,082	1,293,145
Panel B: Winter						
Therms consumed	51.40	54.07	−2.67	49.60	49.94	−0.34
	[33.8]	[35.7]	[34.8]	[31.1]	[33.1]	[31.6]
Days in bill	30.55	30.78	−0.24	30.57	30.83	−0.26
	[1.31]	[1.8]	[1.59]	[1.31]	[1.81]	[1.45]
Allowance	46.70	49.07	−2.37	47.16	49.68	−2.52
	[12.8]	[10.7]	[11.8]	[12.4]	[10.4]	[12]
Total bill	59.79	50.60	9.19	45.35	36.51	8.84
	[41.8]	[36.4]	[39.4]	[30.3]	[26.5]	[29.7]
HDDs	1.69	1.73	−0.04	1.70	1.75	−0.05
(thousands)	[0.467]	[0.437]	[0.452]	[0.439]	[0.422]	[0.435]
N	746,140	800,037	1,546,177	871,795	270,198	1,141,993

Notes: Unbracketed values provide the variables' means; bracketed values denote the variables' standard deviations. The standard deviations below the difference column (*Diff.*) are pooled across utilities. The difference column denotes the difference in means across utilities for the given cross-section of data. For example, the rightmost **Diff.** column in **Panel A** gives the difference between the PG&E mean and the SoCalGas mean for CARE households in summer months, $\bar{X}_{\text{PGE}} - \bar{X}_{\text{SCG}}$. *CARE* households participate in the California Alternative Rates for Energy (CARE) program. CARE targets low-income households and provides a 20 percent discount on natural gas bills. Heating degree days (HDDs) are in thousands. We calculate the number of heating degrees for day t with mean temperature $\bar{T}_t$ (in °F) as $\text{HDD}_t = \mathbb{1}\left\{\bar{T}_t < 65\right\} \times \left(65 - \bar{T}_t\right)$. The HDDs variable above is thus $\text{HDDS} = \sum_t \text{HDD}_t/1000$.

Table 5: **OLS Results**: Estimating elasticities, varying the dataset, price, and fixed effects

	Dependent variable: Log(Consumption, daily avg.)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Marginal price)	0.4698***	0.4346***	0.4276***			
	(0.0106)	(0.0136)	(0.0134)			
Log(Baseline price)				0.0217	−0.0918***	−0.1009***
				(0.0147)	(0.0201)	(0.0209)
Bill HDDs	T	T	T	T	T	T
Household FE	T	T	T	T	T	T
Month-of-sample FE	T	T	F	T	T	F
City by month-of-sample FE	F	F	T	F	F	T
Sample	5% CA	Border	Border	5% CA	Border	Border
N	12,855,910	5,754,088	5,754,088	12,855,910	5,754,088	5,754,088

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing cycle. *Base* or *baseline* price refers to the price the household pays for its first unit (*therm*) of natural gas. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Significance levels:* *10%, **5%, ***1%.

Table 6: **First- and second-stage results**:
Instrumenting consumers' prices with the Henry Hub spot price

Dependent variable: Log(Consumption, daily avg.)					
Panel A: First-stage results					
	(1) Marginal	(2) Average	(3) Avg. Mrg.	(4) Baseline	(5) Sim. Mrg.
Spot price	0.3679***	0.3697***	0.3384***	0.4699***	0.3949***
	(0.0774)	(0.0521)	(0.0570)	(0.0434)	(0.0840)
Spot price × SoCalGas	0.7868***	0.7174***	0.9389***	0.8212***	0.8174***
	(0.0299)	(0.0186)	(0.0198)	(0.0176)	(0.0317)
Panel B: Second-stage results					
Log(Price)	−0.2098***	−0.2312***	−0.1734***	−0.2030***	−0.1705**
(instrumented)	(0.0706)	(0.076)	(0.0585)	(0.065)	(0.0698)
First-stage F stat.	418.4	899.4	1,311.0	1,333.2	369.9
Bill HDDs	T	T	T	T	T
Household FE	T	T	T	T	T
City mo.-of-sample FE	T	T	T	T	T
N	5,754,085	5,754,085	5,754,085	5,754,085	4,682,526

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the houesholds' bill. *(HH) Spot price* refers to the weekly average spot price for natural gas at Louisiana's Henry Hub in the week preceding the utility's price change. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Avg.* or *average* price is the total bill divided by quantity. *Avg. Mrg.* or *average marginal* price denotes the quantity-weighted average of the household's marginal price. *Sim. Mrg.* or *simulated marginal* price is the household's marginal price (using the relevant pricing regime) as a function of the household's historical consumption patterns (lagged bills 10 through 14). As discussed in the empirical strategy section, the numbers of observations differ due to the lags required to calculate the *simulated instrument* for marginal price. *Significance levels:* *10%, **5%, ***1%.

Table 7: **Comparing lags, second-stage results**: Marginal and average prices with HH spot price IV

Dependent variable: Log(Consumption, daily avg.)

	Marginal Price				**Average Price**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1 Lead	No lag	1 Lag	2 Lags	1 Lead	No lag	1 Lag	2 Lags
Log(Price)	0.0480	−0.1121	−0.0223	-0.2098^{***}	0.0515	−0.1244	−0.0177	-0.2312^{***}
instrumented	(0.0902)	(0.0762)	(0.0668)	(0.0706)	(0.0972)	(0.0805)	(0.0730)	(0.0760)
First-stage F stat.	326.7	337.9	410.8	418.4	679.1	725.8	884.4	899.4
Bill HDDs	T	T	T	T	T	T	T	T
Household FE	T	T	T	T	T	T	T	T
City month-of-sample FE	T	T	T	T	T	T	T	T
N	5,501,467	5,754,088	5,754,088	5,754,085	5,501,467	5,754,088	5,754,088	5,754,085

Notes: With regard to lags: *No lag* refers to the price for the household's contemporaneous bill; *1 Lag* refers to the price on the household's previous bill; *etc. Avg.* or *average* price is the total bill divided by quantity. *(HH) Spot price* refers to the weekly average spot price for natural gas at Louisiana's Henry Hub in the week preceding the utility's price change. Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. *Significance levels:* *10%, **5%, ***1%.

Table 8: **Heterogeneity by season or income**:
Second-stage results, instrumenting marginal price with HH spot price

Dependent variable: Log(Consumption, daily avg.)

	Marginal Price			
	Split by **Season**		Split by **CARE (Income)**	
	(1) Summer	(2) Winter	(3) CARE	(4) Non-CARE
Log(Price)	0.0519*	−0.3769***	−0.2443***	−0.1413**
instrumented	(0.0285)	(0.1399)	(0.0794)	(0.0684)
First-stage F stat.	319.6	174.2	393.7	335.8
Bill HDDs	T	T	T	T
Household FE	T	T	T	T
City month-of-sample FE	T	T	T	T
N	3,065,917	2,688,168	2,435,135	3,318,950

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Summer* includes April through September. *Winter* includes October through March. *CARE* households participate in the California Alternative Rates for Energy (CARE) program. CARE targets low-income households and provides a 20 percent discount on natural gas bills. We estimate the heterogeneity results by splitting the sample along the dimension(s) of heterogeneity and then individually estimating the models. *Significance levels:* *10%, **5%, ***1%.

Table 9: **Heterogeneity by season and income**:
Second-stage results, instrumenting marginal price with HH spot price

Dependent variable: Log(Consumption, daily avg.)

	Marginal Price			
	(1) Summer CARE	(2) Summer Non-CARE	(3) Winter CARE	(4) Winter Non-CARE
Log(Price)	0.0457	0.0742**	−0.5226***	−0.3173**
instrumented	(0.0353)	(0.0324)	(0.1424)	(0.1498)
First-stage F stat.	303.4	237.1	145.6	156.7
Bill HDDs	T	T	T	T
Household FE	T	T	T	T
City month-of-sample FE	T	T	T	T
N	1,293,144	1,772,773	1,141,991	1,546,177

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Summer* includes April through September. *Winter* includes October through March. *CARE* households participate in the California Alternative Rates for Energy (CARE) program. CARE targets low-income households and provides a 20 percent discount on natural gas bills. We estimate the heterogeneity results by splitting the sample along the dimension(s) of heterogeneity and then individually estimating the models. *Significance levels:* *10%, **5%, ***1%.

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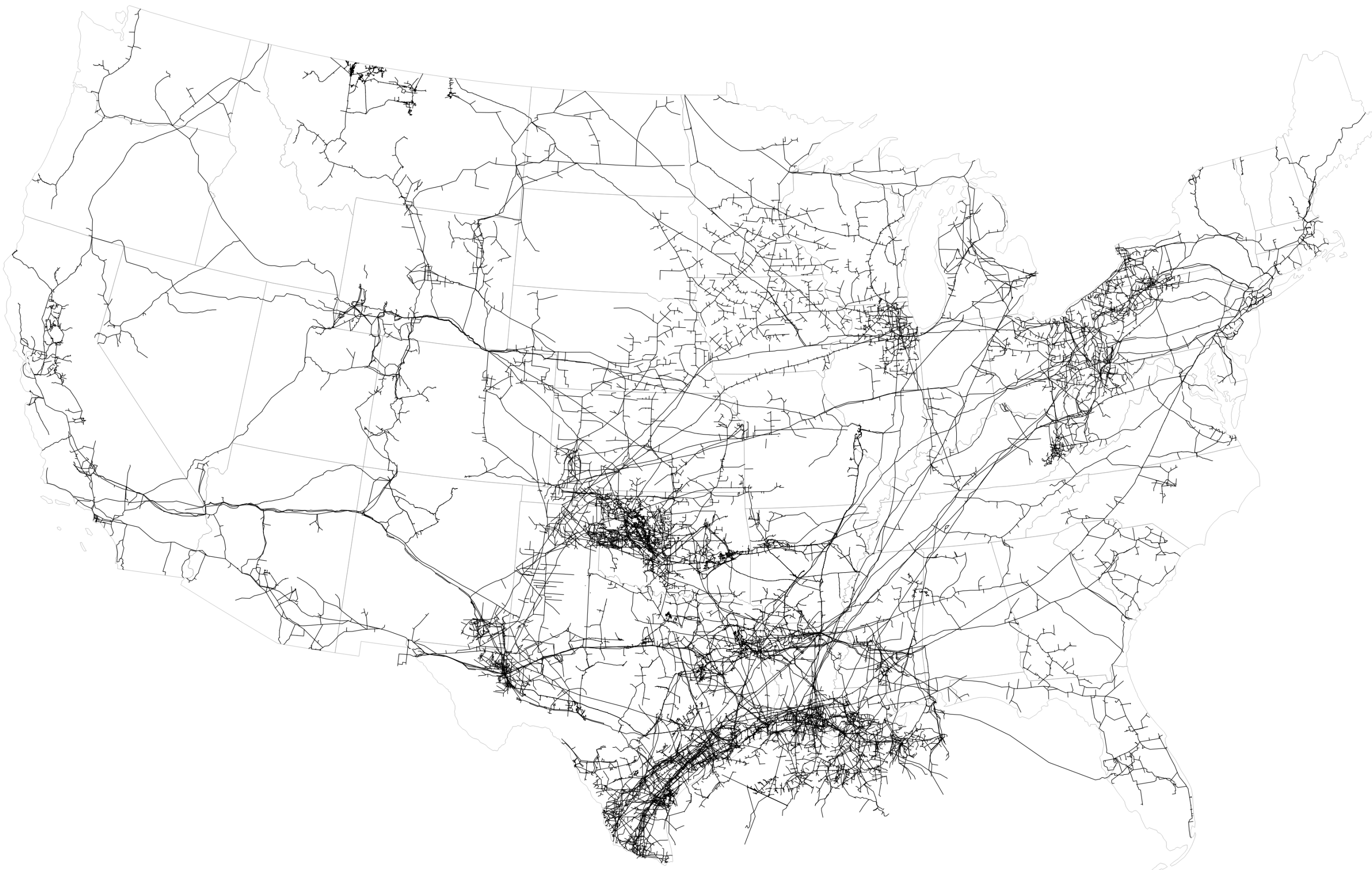
A Appendix

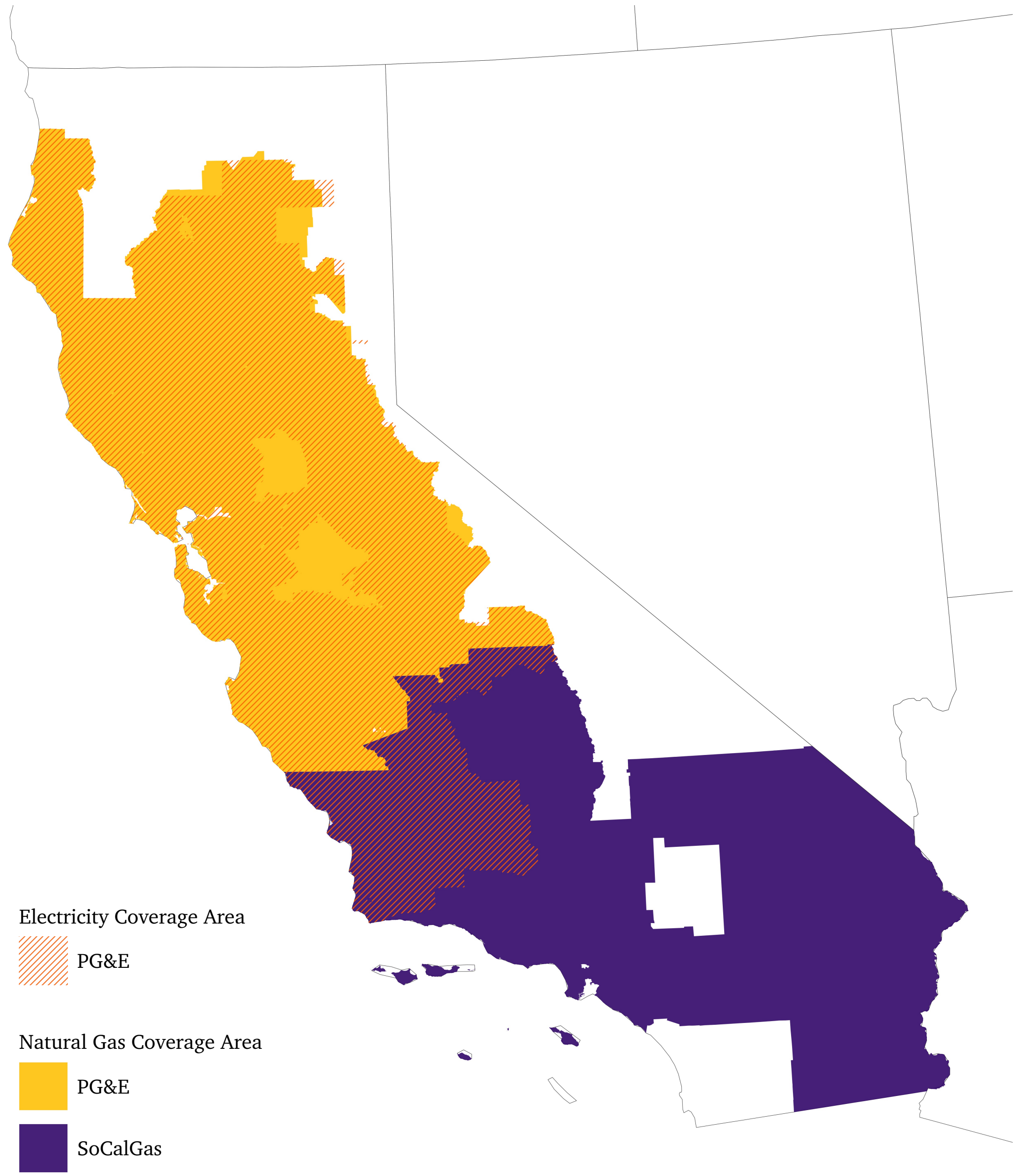
A.1 Appendix figures

Figure A1: **U.S. natural gas pipeline network**



Notes: This map depicts the intra- and inter-state natural gas pipeline network for the (continental) United States (in black) overlayed on a map of the (continental) U.S. (light gray). *Source:* U.S. Energy Information Administration

Figure A2: **Natural gas service areas and PG&E's electricity service area**



Notes: This map illustrates the natural gas service areas covered by PG&E (darker purple) and SoCalGas (lighter gold), as well as PG&E's service area for electricity (diagonally hashed pink). PG&E's electricity service covers both sides of the natural-gas service area. This overlap allows two neighboring households to receive natural gas from two different utilities, while they both receive electricity from PG&E. Note that this map differs slightly from Figure 4 because this map uses the official boundaries from California Energy Commission, whereas Figure 4 maps zip codes contained in our billing data.

Figure A3: **California's 16 CEC climate zones** determine daily allowance within season

Notes: The shapefile underlying this map comes from the California Energy Commission (CEC). This map constitutes the CEC's climate-based building zones, which affect a number of energy policies, including households' baseline allowances. (California Energy Commission 2015, 2017)

Figure A4: **Example bill:** PG&E residential natural gas bill

PG&E

ENERGY STATEMENT

www.pge.com/MyEnergy

Account No:	[redacted]
Statement Date:	12/25/2016
Due Date:	**01/17/2017**

Details of Gas Charges

11/24/2016 - 12/23/2016 (30 billing days)

Service For: [redacted]
Service Agreement ID: [redacted]
Rate Schedule: G1 T Residential Service

11/24/2016 – 11/30/2016 Your Tier Usage | **1** | 2 |

Tier 1 Allowance	12.53 Therms	(7 days x 1.79 Therms/day)	
Tier 1 Usage	2.333330 Therms @ $1.42692		$3.33
Gas PPP Surcharge ($0.10197 /Therm)			0.24
Berkeley Utility Users' Tax (7.500%)			0.25

12/01/2016 – 12/23/2016 Your Tier Usage | **1** | 2 |

Tier 1 Allowance	41.17 Therms	(23 days x 1.79 Therms/day)	
Tier 1 Usage	7.666670 Therms @ $1.36245		$10.45
Gas PPP Surcharge ($0.10197 /Therm)			0.78
Berkeley Utility Users' Tax (7.500%)			0.78

Total Gas Charges **$15.83**

Service Information

Meter #	[redacted]
Current Meter Reading	3,036
Prior Meter Reading	3,026
Difference	10
Multiplier	1.046971
Total Usage	10.000000 Therms
Baseline Territory	T
Serial	C

Gas Procurement Costs ($/Therm)

11/24/2016 - 11/30/2016	$0.45875
12/01/2016 - 12/23/2016	$0.39428

Notes: This 30-day bill for a PG&E customer (one of the authors) overlaps two calendar months in 2016: 7 days in November (24–30) and 23 days in December (01–23). Because PG&E's prices vary with the calendar month, PG&E needs to split consumption by calendar month. To achieve this task, PG&E assumes the customer consumed evenly across all days in the bill. Specifically, PG&E calculates that the customer consumed 10 therms and assigns the same amount of consumption to each day during the 30-day period. Thus, PG&E assigns $10 \times 7/30 \approx 2.33$ to November (the consumer spent 7 days in November in this 30-day bill) and $10 \times 23/30 \approx 7.67$ to December (the consumer spent 23 days in November in this 30-day bill).

Figure A5: **PRISM:** Mean temperature raster for 15 June 2010

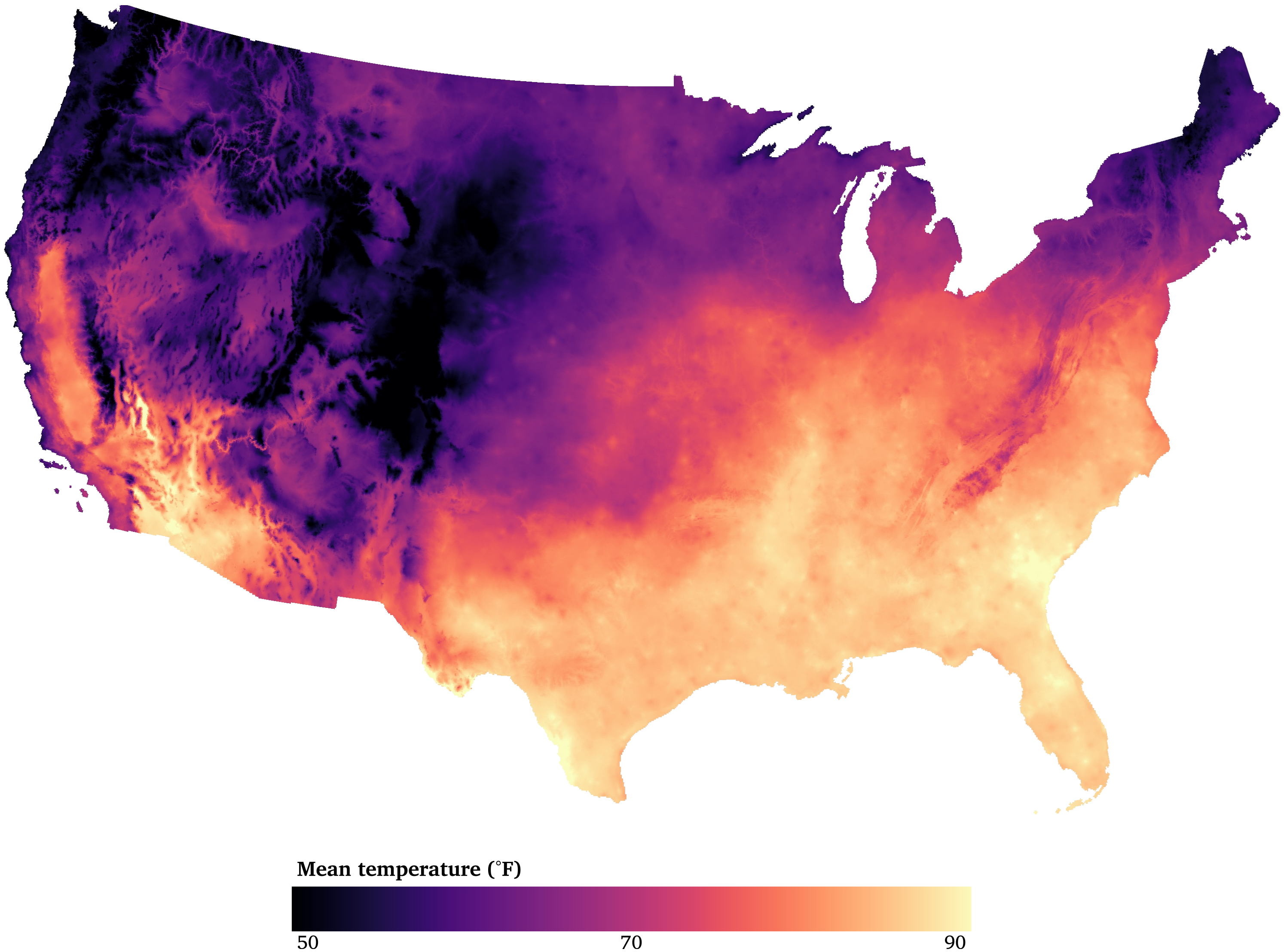
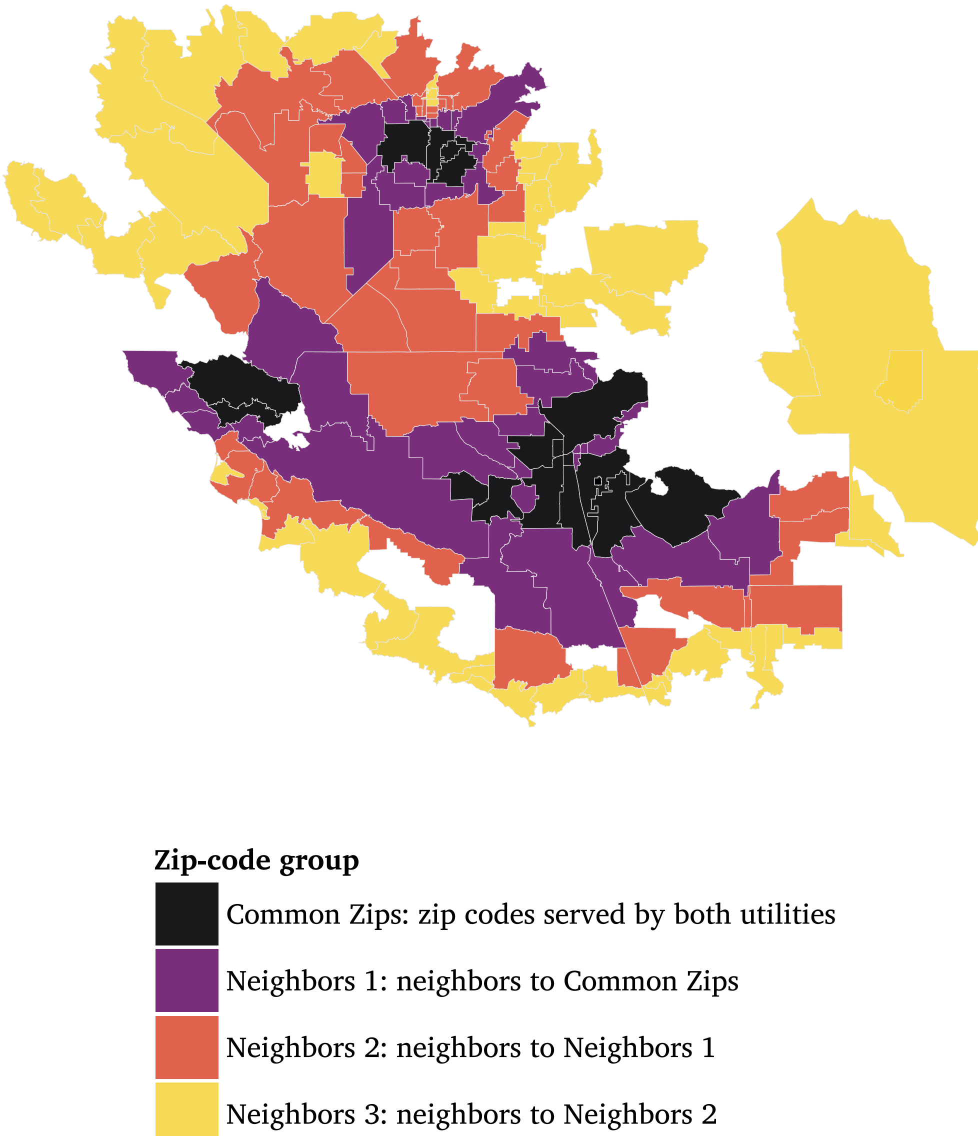


Figure A6: **Expanding the study area:** Zip codes neighboring the study's zip codes



Notes: This figure illustrates the four groups of zip codes referenced in Table A16. The groups begin with *Common Zips*—the group in which each zip code receives natural gas service from both PG&E and SoCalGas—and expands by adding each group's immediately proximate neighbors. *E.g.*, *Neighbors 2* consists of all zip codes that neighbor a zip code in *Neighbors 1* (excluding those zip codes already included in another group).

A.2 Appendix tables

Table A1: **Price correlation**: Bivariate correlations between types of prices

	Type of Price				
	Marginal	Average	Avg. Mrg.	Baseline	Sim. mrg.
Marginal	1				
Average	0.8898	1			
Avg. Mrg.	0.8628	0.9421	1		
Baseline	0.7901	0.942	0.9202	1	
Sim. mrg.	0.8503	0.849	0.8174	0.781	1

Notes: *Avg.* or *average* price is the total bill divided by quantity. *Avg. Mrg.* or *average marginal* price denotes the quantity-weighted average of the household's marginal price. *Base* or *baseline* price refers to the price the household pays for its first unit (*therm*) of natural gas. *Sim. Mrg.* or *simulated marginal* price is the household's marginal price (using the relevant pricing regime) as a function of the household's historical consumption patterns (lagged bills 10 through 14).

Table A2: **Testing the simulated instrument**:
Regressing marginal price on *simulated* marginal price

Dependent variable: Marginal price

	(1)	(2)
Simulated marginal price	0.6425***	0.6444***
	(0.00435)	(0.00433)
Bill HDDs	T	T
Household FE	T	T
City month-of-sample FE	T	T
Lags used for sim. inst.	10–14	11–13
N	4,892,064	4,785,877

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. *Sim. Mrg.* or *simulated marginal* price is the household's marginal price (using the relevant pricing regime) as a function of the household's historical consumption patterns (lagged bills 10 through 14 or 11 through 13). As discussed in the empirical strategy section, the numbers of observations differ due to the lags required to calculate the *simulated instrument* for marginal price. *Significance levels:* *10%, **5%, ***1%.

Table A3: **Comparing lags, second-stage results**: Marginal price with HH spot price IV

Dependent variable: Log(Consumption, daily avg.)

	Lag of Marginal Price				
	(1) 1 Lead	(2) No lag	(3) 1 Lag	(4) 2 Lags	(5) 3 Lags
Log(Price)	0.0480	−0.1121	−0.0223	−0.2098***	−0.1582**
instrumented	(0.0902)	(0.0762)	(0.0668)	(0.0706)	(0.0698)
First-stage F stat.	326.7	337.9	410.8	418.4	403.4
Bill HDDs	T	T	T	T	T
Household FE	T	T	T	T	T
City month-of-sample FE	T	T	T	T	T
N	5,501,467	5,754,088	5,754,088	5,754,085	5,754,079

Notes: With regard to lags: *No lag* refers to the price for the household's contemporaneous bill; *1 Lag* refers to the price on the household's previous bill; *etc. (HH) Spot price* refers to the weekly average spot price for natural gas at Louisiana's Henry Hub in the week preceding the utility's price change. Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. *Significance levels:* *10%, **5%, ***1%.

Table A4: **Comparing lags, second-stage results**: Sim. marginal price with HH spot price IV

Dependent variable: Log(Consumption, daily avg.)

	Lag of Simulated Marginal Price				
	(1) 1 Lead	(2) No lag	(3) 1 Lag	(4) 2 Lags	(5) 3 Lags
Log(Price)	0.0317	−0.0549	0.0329	−0.1705**	−0.1596**
instrumented	(0.0899)	(0.0718)	(0.0626)	(0.0698)	(0.0720)
First-stage F stat.	354.7	379.6	393.2	369.9	332.1
Bill HDDs	T	T	T	T	T
Household FE	T	T	T	T	T
City month-of-sample FE	T	T	T	T	T
N	4,778,382	4,892,064	4,785,877	4,682,526	4,590,790

Notes: With regard to lags: *No lag* refers to the price for the household's contemporaneous bill; *1 Lag* refers to the price on the household's previous bill; *etc. Sim. Mrg.* or *simulated marginal* price is the household's marginal price (using the relevant pricing regime) as a function of the household's historical consumption patterns (lagged bills 10 through 14). *(HH) Spot price* refers to the weekly average spot price for natural gas at Louisiana's Henry Hub in the week preceding the utility's price change. Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. *Significance levels:* *10%, **5%, ***1%.

Table A5: **Comparing lags, second-stage results**: Avg. marginal price with HH spot price IV

Dependent variable: Log(Consumption, daily avg.)

	Lag of Average Marginal Price				
	(1) 1 Lead	(2) No lag	(3) 1 Lag	(4) 2 Lags	(5) 3 Lags
Log(Price)	0.0432	−0.0853	−0.0313	-0.1734^{***}	-0.1356^{**}
instrumented	(0.0745)	(0.0618)	(0.0568)	(0.0585)	(0.0585)
First-stage F stat.	969.4	1,036.4	1,275.3	1,311.0	1,306.1
Bill HDDs	T	T	T	T	T
Household FE	T	T	T	T	T
City month-of-sample FE	T	T	T	T	T
N	5,501,467	5,754,088	5,754,088	5,754,085	5,754,079

Notes: With regard to lags: *No lag* refers to the price for the household's contemporaneous bill; *1 Lag* refers to the price on the household's previous bill; *etc. Sim. Mrg.* or *simulated marginal* price is the household's marginal price (using the relevant pricing regime) as a function of the household's historical consumption patterns (lagged bills 10 through 14). *(HH) Spot price* refers to the weekly average spot price for natural gas at Louisiana's Henry Hub in the week preceding the utility's price change. Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. *Significance levels:* *10%, **5%, ***1%.

Table A6: **Comparing lags, second-stage results**: Avgerage price with HH spot price IV

Dependent variable: Log(Consumption, daily avg.)

	Lag of Average Price				
	(1) 1 Lead	(2) No lag	(3) 1 Lag	(4) 2 Lags	(5) 3 Lags
Log(Price)	0.0515	−0.1244	−0.0177	-0.2312^{***}	-0.1680^{**}
instrumented	(0.0972)	(0.0805)	(0.0730)	(0.0760)	(0.0749)
First-stage F stat.	679.1	725.8	884.4	899.4	923.7
Bill HDDs	T	T	T	T	T
Household FE	T	T	T	T	T
City month-of-sample FE	T	T	T	T	T
N	5,501,467	5,754,088	5,754,088	5,754,085	5,754,079

Notes: With regard to lags: *No lag* refers to the price for the household's contemporaneous bill; *1 Lag* refers to the price on the household's previous bill; *etc. Avg.* or *average* price is the total bill divided by quantity. *(HH) Spot price* refers to the weekly average spot price for natural gas at Louisiana's Henry Hub in the week preceding the utility's price change. Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. *Significance levels:* *10%, **5%, ***1%.

Table A7: **Comparing lags, second-stage results**: Baseline price with HH spot price IV

Dependent variable: Log(Consumption, daily avg.)

	Lag of Baseline Price				
	(1) 1 Lead	(2) No lag	(3) 1 Lag	(4) 2 Lags	(5) 3 Lags
Log(Price)	0.0420	-0.1164^{*}	-0.0066	-0.2030^{***}	-0.1396^{**}
instrumented	(0.0839)	(0.0684)	(0.0637)	(0.0650)	(0.0630)
First-stage F stat.	1,085.3	1,143.4	1,241.8	1,333.2	1,533.2
Bill HDDs	T	T	T	T	T
Household FE	T	T	T	T	T
City month-of-sample FE	T	T	T	T	T
N	5,501,467	5,754,088	5,754,088	5,754,085	5,754,079

Notes: With regard to lags: *No lag* refers to the price for the household's contemporaneous bill; *1 Lag* refers to the price on the household's previous bill; *etc. Base* or *baseline* price refers to the price the household pays for its first unit (*therm*) of natural gas. *(HH) Spot price* refers to the weekly average spot price for natural gas at Louisiana's Henry Hub in the week preceding the utility's price change. Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. *Significance levels:* *10%, **5%, ***1%.

Table A8: **Heterogeneity by season or income**:
Second-stage results, instrumenting average price with HH spot price

	Dependent variable: Log(Consumption, daily avg.)			
	Average Price			
	Split by **Season**		Split by **CARE (Income)**	
	(1) Summer	(2) Winter	(3) CARE	(4) Non-CARE
Log(Price)	0.0579*	−0.4694***	−0.2650***	−0.1557**
instrumented	(0.0316)	(0.1586)	(0.0834)	(0.0740)
First-stage F stat.	765.7	223.4	814.7	745.8
Bill HDDs	T	T	T	T
Household FE	T	T	T	T
City month-of-sample FE	T	T	T	T
N	3,065,917	2,688,168	2,435,135	3,318,950

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. *Summer* includes April through September. *Winter* includes October through March. *CARE* households participate in the California Alternative Rates for Energy (CARE) program. CARE targets low-income households and provides a 20 percent discount on natural gas bills. We estimate the heterogeneity results by splitting the sample along the dimension(s) of heterogeneity and then individually estimating the models. *Avg.* or *average* price is the total bill divided by quantity. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Significance levels:* *10%, **5%, ***1%.

Table A9: **Heterogeneity by season and income**:
Second-stage results, instrumenting average price with HH spot price

Dependent variable: Log(Consumption, daily avg.)

	Average Price			
	(1) Summer CARE	(2) Summer Non-CARE	(3) Winter CARE	(4) Winter Non-CARE
Log(Price) *instrumented*	0.0495 (0.0384)	0.0828** (0.0359)	−0.6106*** (0.1570)	−0.3971** (0.1687)
First-stage F stat.	691.5	591.9	212.7	184.8
Bill HDDs	T	T	T	T
Household FE	T	T	T	T
City month-of-sample FE	T	T	T	T
N	1,293,144	1,772,773	1,141,991	1,546,177

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Summer* includes April through September. *Winter* includes October through March. *CARE* households participate in the California Alternative Rates for Energy (CARE) program. CARE targets low-income households and provides a 20 percent discount on natural gas bills. We estimate the heterogeneity results by splitting the sample along the dimension(s) of heterogeneity and then individually estimating the models. *Avg.* or *average* price is the total bill divided by quantity. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Significance levels:* *10%, **5%, ***1%.

Table A10: **First-stage results**:
Robustness to specification: Marginal price instrumented with spot price

Dependent variable: Log(Marginal price)				
	(1)	(2)	(3)	(4)
Spot price	0.3398***	0.3679***	0.3806***	0.3955***
	(0.0757)	(0.0774)	(0.0798)	(0.0547)
Spot price × SoCalGas	0.7858***	0.7868***	0.7856***	0.7385***
	(0.0300)	(0.0299)	(0.0302)	(0.0378)
First-stage F stat.	416.1	418.4	415.2	367.0
Bill HDDs	F	T	T	T
Household FE	T	T	T	T
City by month-of-sample FE	T	T	F	F
City by week-of-sample FE	F	F	T	F
Zip by week-of-sample FE	F	F	F	T
N	5,754,085	5,754,085	5,754,085	5,754,085

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *(HH) Spot price* refers to the weekly average spot price for natural gas at Louisiana's Henry Hub in the week preceding the utility's price change. *Significance levels:* *10%, **5%, ***1%.

Table A11: **Second-stage results**:
Robustness to specification: Marginal price instrumented with spot price

Dependent variable: Log(Consumption, daily avg.)				
	(1)	(2)	(3)	(4)
Log(Marginal price)	−0.3623***	−0.2098***	−0.1705***	−0.1495**
instrumented	(0.0854)	(0.0706)	(0.0621)	(0.063)
First-stage F stat.	416.1	418.4	415.2	367.0
Bill HDDs	F	T	T	T
Household FE	T	T	T	T
City by month-of-sample FE	T	T	F	F
City by week-of-sample FE	F	F	T	F
Zip by week-of-sample FE	F	F	F	T
N	5,754,085	5,754,085	5,754,085	5,754,085

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Significance levels:* *10%, **5%, ***1%.

Table A12: **Second-stage results**:
Robustness to specification: Average price instrumented with spot price

Dependent variable: Log(Consumption, daily avg.)				
	(1)	(2)	(3)	(4)
Log(Average price)	-0.4076^{***}	-0.2312^{***}	-0.1891^{***}	-0.1574^{**}
instrumented	(0.0911)	(0.076)	(0.067)	(0.0656)
First-stage F stat.	897.5	899.4	881.1	661.1
Bill HDDs	F	T	T	T
Household FE	T	T	T	T
City by month-of-sample FE	T	T	F	F
City by week-of-sample FE	F	F	T	F
Zip by week-of-sample FE	F	F	F	T
N	5,754,085	5,754,085	5,754,085	5,754,085

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Avg.* or *average* price is the total bill divided by quantity. *Significance levels:* *10%, **5%, ***1%.

Table A13: **Second-stage results**:
Robustness to specification: Avg. mrg. price instrumented with spot price

Dependent variable: Log(Consumption, daily avg.)				
	(1)	(2)	(3)	(4)
Log(Avg. marginal price)	-0.2951^{***}	-0.1734^{***}	-0.1529^{***}	-0.1330^{**}
instrumented	(0.0697)	(0.0585)	(0.0514)	(0.0549)
First-stage F stat.	1,299.9	1,311.0	1,275.8	780.6
Bill HDDs	F	T	T	T
Household FE	T	T	T	T
City by month-of-sample FE	T	T	F	F
City by week-of-sample FE	F	F	T	F
Zip by week-of-sample FE	F	F	F	T
N	5,754,085	5,754,085	5,754,085	5,754,085

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Avg. Mrg.* or *average marginal* price denotes the quantity-weighted average of the household's marginal price. *Significance levels:* *10%, **5%, ***1%.

Table A14: **Second-stage results**:
Robustness to specification: Baseline price instrumented with spot price

Dependent variable: Log(Consumption, daily avg.)

	(1)	(2)	(3)	(4)
Log(Simulated mrg. price)	-0.3148^{***}	-0.1705^{**}	-0.1310^{**}	-0.1025
instrumented	(0.0843)	(0.0698)	(0.0602)	(0.0675)
First-stage F stat.	368.9	369.9	331.3	181.9
Bill HDDs	F	T	T	T
Household FE	T	T	T	T
City by month-of-sample FE	T	T	F	F
City by week-of-sample FE	F	F	T	F
Zip by week-of-sample FE	F	F	F	T
N	4,682,526	4,682,526	4,682,526	4,682,526

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Sim. Mrg.* or *simulated marginal* price is the household's marginal price (using the relevant pricing regime) as a function of the household's historical consumption patterns (lagged bills 10 through 14). *Significance levels:* *10%, **5%, ***1%.

Table A15: **Second-stage results**:
Robustness to specification: Baseline price instrumented with spot price

Dependent variable: Log(Consumption, daily avg.)

	(1)	(2)	(3)	(4)
Log(Baseline price)	-0.3643^{***}	-0.2030^{***}	-0.1653^{***}	-0.1376^{**}
instrumented	(0.077)	(0.065)	(0.0576)	(0.0572)
First-stage F stat.	1,322.9	1,333.2	1,187.3	762.5
Bill HDDs	F	T	T	T
Household FE	T	T	T	T
City by month-of-sample FE	T	T	F	F
City by week-of-sample FE	F	F	T	F
Zip by week-of-sample FE	F	F	F	T
N	5,754,085	5,754,085	5,754,085	5,754,085

Notes: Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Base* or *baseline* price refers to the price the household pays for its first unit (*therm*) of natural gas. *Significance levels:* *10%, **5%, ***1%.

Table A16: **Second-stage results**: Extending the set of zip codes to neighboring zip codes

Dependent variable: Log(Consumption, daily avg.)

	Marginal Price			
	(1) Common Zips	(2) Neighbors 1	(3) Neighbors 2	(4) Neighbors 3
Log(Marginal price)	-0.2098^{***}	-0.1896^{***}	-0.1241^{***}	-0.0946^{***}
instrumented	(0.0706)	(0.049)	(0.0401)	(0.0357)
First-stage F stat.	418.4	713.0	735.8	1,182.9
Bill HDDs	T	T	T	T
Household FE	T	T	T	T
City by month-of-sample FE	T	T	T	T
Levels of neighboring zip codes	0	1	2	3
N	5,754,085	11,679,371	19,629,128	28,277,567

Notes: *Common zips* refers the set of zip codes in which each zip code receives natural gas from both PG&E and SoCalGas. *Neighbors 1* includes the *common zips* and the zip codes that immediately neighbor the common zips. *Neighbors 2* adds the neighbors of these neighbors (adding the neighbors of *Neighbors 1*). *Neighbors 3* adds the neighbors of *Neighbors 2*. Figure A6 depicts these sets of zip codes. Each column denotes a separate regression. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle (the level at which price varies). All regressions include heating degree days (HDDs) within the households' billing period. Each price in the table is the second lag of price, *i.e.*, the prices from two bills prior to the current bill. *Significance levels:* *10%, **5%, ***1%.

Table A17: **Billing data description:** Columns within the billing data

Feature name	**Description**
Account ID	Unique identifier for household account with the utility
Premise ID	Unique physical-location based identifier
Prior read date	Effectively the start date of the bill
Current read date	Effectively the end date of the bill
Gas rate schedule	Classifies type of customer (and the customer's price regime)
Gas usage	Volume of gas consumed during billing period (in therms)
Bill revenue	Total bill charged to household for the current billing period
Climate band	California Public Utility Commission-based climate region
Service address 9-digit zip	Household's 9-digit zip code
Service start date	Date on which the household began service
Service stop date	Date on which the household ended service

A.3 Calculating bills

As discussed in the body of the paper, the majority of bills do not line up with calendar months. Consequently, households' billing periods do not line up with utilities' monthly changes in price (or with changes in daily allowances resulting from changes in seasons). Thus, a single bill will typically span multiple price regimes. The two utilities deal with change in price in subtly different ways. This "problem" results from the fact that neither utility knows households' *daily* consumption.

PG&E When a PG&E customer's bill spans multiple calendar months (price regimes), PG&E calculates individual bills for each month. However, because PG&E does not know the daily consumption levels, they assume constant daily consumption throughout the billing period.

SoCalGas In the case that a SoCalGas customer's bill spans multiple calendar months (price regimes), SoCalGas computes time-weighted average prices (and allowances) by aggregating the prices and allowances from the calendar months by the number of days the bill spent in each month.

A.4 Data work

In this section, we describe the exclusion and cleaning choices that we made while preparing the data for analysis. Our R scripts are available upon request, though the data themselves cannot be shared due to agreements with the utilities and the IRB.

Exclusions:

- We omitted SoCalGas price data from advice letters 3644, 3680, 3695, 3807, 4053, and 4061, as they were updated by letters 3660, 3697, 3697, 3810, 4055, and 4069, respectively.
- We dropped pre-2008 data (PG&E and prices/allowances), as SoCalGas did not share billing data for pre-2009 bills.
- We trimmed the shortest 2.5% and longest 2.5% bills (resulted in keeping bills of length between 28-34 days). We did this to omit the first or last bills for a household and bills

that were irregular for any other reasons. We applied this requirement of 28–34 days to the current bill and the first through the third lagged bills, because we consider the effect of lagged prices on contemporaneous consumption.

- We dropped bills missing any critical information: number of therms (quantity), revenue, *etc.*
- We dropped bills outside the central 99% of data (*i.e.*, the bill's revenue or volume fall in the bottom 0.5% or in the top 0.5%). Our main results apply this rule for the contemporaneous and the first three lagged bills.
- We dropped bills whose total revenue we could not predict within five percent (using known prices, quantities, and discounts).
- We dropped bills for exactly zero therms.

CARE status While the datasets presumably denoted CARE (California Alternate Rates for Energy) households, we found many households not denoted as CARE households whose charges were consistent with CARE pricing (*i.e.*, charges were 80 percent of the standard tariffs). We classified these households as CARE households.