Natural gas elasticities and optimal cost recovery under heterogeneity: Evidence from 300 million natural gas bills*

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Abstract

In 2016 natural gas became the United States' primary source of energy for electricity generation. It is also the main heating fuel for more than 50% of American homes. Hence understanding residential natural gas consumption behavior has become a first-order problem. In this paper, we provide the first ever causally identified, microdata-based estimates of residential natural gas demand elasticities using a decade-long panel of approximately 300 million bills in California. To overcome multiple sources of endogeneity, we employ a two-pronged empirical strategy: (1) we exploit a discontinuity along the border between two major natural-gas utilities in conjunction with (2) an instrumental variables strategy based upon the differences in the utilities' rules/behaviors for internalizing changes in the upstream natural gas spot market. We estimate the elasticity of demand for residential natural gas is between −0.31 and −0.17. We also provide evidence of seasonal and income-based heterogeneity in this elasticity. This heterogeneity provides unexplored policy avenues that may be simultaneously efficiency-enhancing and pro-poor.

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I. Introduction

Throughout the 20th century, coal dominated all other fossil fuels, powering the unprecedented economic transformation of the United States and many other economies. However, due to the invention and broad rollout of a new technology to extract gas from below the surface—hydraulic fracturing ("frac(k)ing")—it appears as though cheap natural gas will power the first half of the 21st century. Specifically, in 2005, hydraulic fracturing 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]. Since 2005, natural gas production in the United States has expanded dramatically, and natural gas prices have fallen considerably—often residing at half of their 2005 levels (see Figure 1 and Hausman and Kellogg 2015). In 2016, natural gas surpassed coal as the main source of energy for electricity generation in the United States U.S. Energy Information Administration 2016a. Further, natural gas is the main heating fuel for more than half of US residences. The US Energy Information Administration (EIA) estimates that energy-related carbon dioxide (CO_2) emissions from natural gas overtook energy-related CO_2 emissions from coal in 2016 [U.S. Energy Information Administration 2016b].

The low price of natural gas and its recently abundant volumes, coupled with natural gas's status as the cleanest and most efficient fossil fuel [National Academy of Sciences 2016; Levine, Carpenter, and Thapa 2014], have certainly garnered broad public and policy support for natural gas.[1] Due to its low carbon content per BTU, natural gas is often regarded as a "bridge fuel"—*bridging* society toward a future mainly powered by largely carbon-free sources of renewable energy. However, natural gas is not without critics—particularly natural gas that results from hydraulic fracturing. The most common criticisms of current natural gas policy relate to environmental degradation—ranging from groundwater contamination to the triggering small earthquakes. More broadly, researchers have also critiqued inefficient and potentially regressive pricing (and regulatory) regimes used on the consumer-facing side of the industry [Borenstein and Davis 2012; Davis and Muehlegger 2010].

In this paper, we provide the first causally identified, micro-data based estimates of the

[1] 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].

elasticity of demand for residential natural gas. This parameter estimate contributes to a body of natural gas research requiring a precise and well-identified estimate of the price elasticity of demand of natural gas; these topics range from the welfare implications of the United States' natural gas boom to hydraulic fracturing's environmental impact to the efficiency and distribution of natural gas's prevailing pricing and regulatory standards [Davis and Muehlegger 2010; Hausman and Kellogg 2015]. Despite this policy relevance, there is a relative dearth of well-identified estimates for the own-price elasticity of the demand for natural gas. 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.[2] Perhaps more importantly, we are unable to find published research that pairs consumer-level data with appropriate identification strategies to estimate a price elasticity of demand for natural that carries a causal interpretation.

This paper draws upon a dataset of approximately 300 million residential natural gas bills in California, which provides us with the requisite power and detail to resolve multiple sources of endogeneity and identify pooled and heterogeneous price elasticities. In order to avoid the potential biases from the sources of endogeneity discussed below, we employ a two-pronged identification strategy. The first prong of our identification strategy exploits a spatial discontinuity based upon the boundary between the service areas of two large natural gas utilities. The second prong interacts this spatial discontinuity with a *supply-shifting* instrumental variables (IV) approach—instrumenting 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*). As a result of this two-part empirical strategy—coupled with the rich set of fixed effects that our dataset allows—the identifying variation in the residential price of natural gas comes from (1) on which side of a long-established border the household is located, and (2) the subtly different pricing rules governing the two rate-of-return-earning utilities as they each respond to variations in the natural gas spot market. This approach yields an estimate for the price elasticity of demand for residential natural gas of approximately -0.26.

[2]The authors performed these searches in January 2017.

In addition, we find evidence of heterogeneity in this elasticity along two economically important and statistically significant dimensions: season and income. Lower-income households and higher-income households both are essentially inelastic to price in summer months. In winter months, however, lower-income households are substantially more elastic to prices than higher-income households. In addition to providing motivation for unexplored policies with the potential to be both efficiency enhancing and pro-poor, these heterogeneity findings also supply insights into other *pooled* elasticity estimates that do not consider heterogeneity.

While the natural-gas demand elasticity literature is sparse relative to that of the electricity literature [Rehdanz 2007], several previous papers offer estimates for the price elasticity of demand for residential natural gas. Table 1 lists the past studies that we found, the type of data 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; Davis and Muehlegger) or using micro data with *average* prices (*e.g.*, Alberini, Gans, and Velez-Lopez 2011; Meier and Rehdanz 2010). The exception is Rehdanz, who uses a two-period sample from West Germany, where it appears average price equalled marginal price. The majority of these papers do not attempt to deal with bias resulting from multiple sources of simultaneity, which we discuss below.

Researchers in this area face two major challenges: insufficient data and multiple potential sources of endogeneity. Many of the available datasets aggregate consumption across both space and time. This aggregation—coupled with utilities' multi-tiered volumetric pricing regimes, income-based discounts, and fixed charges—makes it impossible for researchers to match consumers to the actual prices they face. Aggregation across customers and seasons also inhibits research into heterogeneity across consumers. Perhaps most importantly, research on 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 result from the equilibrium in a system of equations. This is due to the fact that that unlike the electricity sector, rates customers pay change on a monthly basis as a function of gas wholesale prices. The second source of endogeneity results from the fact that price is mechanically a function of quantity in a block-rate price regime. As a household's consumption increases, its marginal price also increase (consequently, its average price also increases).

II. Institutional setting

In this section we describe the basic organization of the natural gas industry, breaking the market into four segments: (1) production and processing, (2) transportation, (3) storage, and (4) local distribution companies (LDCs). Figure 2 illustrates the basic institutional organization of the natural gas industry.[3] The four segments we discuss below roughly follow Figure 2 except that they exclude end users, those who simply 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 greater 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 in this paper.

A. 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 (separating "natural gas" from "natural gas liquids") [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). Private companies own and operate segments of the pipelines; these pipeline companies'

[3] 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.

rates are regulated at the state level and the national level [Levine, Carpenter, and Thapa 2014]. The term *citygate price* refers to the price that LDCs pay for natural gas. Extensive spot markets and futures markets exist for natural gas. 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 contract [Levine, Carpenter, and Thapa 2014]. Figure 1 depicts the Henry Hub spot price from 1997 through 2016. Transportation costs represent a substantial percentage of natural gas prices: according to Levine, Carpenter, and Thapa, in 2011–2012, 72 percent of consumers' average heating costs originated in "transmission and distribution charges".[4] This transportation network creates a nationally integrated market and simultaneously contributes to a sizable portion of natural gas end-users' prices.

Storage Storage plays a major role in several parts the natural gas market, but all parties store mainly for the same reason: volatility within the market. Due to its major role 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 in underground storage [Levine, Carpenter, and Thapa 2014]. Producers utilize storage to smooth production.

Local distribution companies Local distribution companies' primary function is distributing 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 (CPUC)) regulate LDC's price

[4]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.

regimes, allowing the LDCs to earn a regulated rate of return [Brown and Yücel 1993; Davis and Muehlegger 2010; Levine, Carpenter, and Thapa 2014].

B. Natural gas pricing in California

The California Public Utilities Commission (CPUC) regulates both of the utilities from whom we draw our data in this paper—Pacific Gas and Electric Company (PG&E) and Southern California Gas Company (SoCalGas). Because this paper analyzes 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) define geographic climate zones [California Energy Commission 2015, 2017], which also determines households' price schedules.

For PG&E's and SoCalGas's residential consumers, a household's bill depends upon five elements:[5]

1. The price schedule set by the utility
2. The total volume of natural gas consumed during the bill period
3. The season 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

Figure 8 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 (CEC) 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

[5]Consumers' billing periods do not perfectly align with calendar months. However, PG&E's and SoCalGas's price changes 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. These methods would be equivalent under a single linear price but differ under the actual multi-tiered regimes. Please see the *Calculating bills* section in the appendix for more detail.

should be adequate for heating during the course of one day. This volume 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) 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*).[6] Figure 3 illustrates an example of the two-tier block-pricing regime used by PG&E and SoCalGas. Figure 4 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 6 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.[7] These monthly price changes allow the utilities to charge customers at rates that reflect the prevailing price of natural gas—the utilities' cost—and are in fact tied to the utilities' costs, which directly correspond to spot market prices. If the utilities wish to change 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 5 illustrates these monthly price-regime changes and the fairly fixed step between the two tiers.

A household's CARE (California Alternate Rates for Energy) status also affects the prices that the household faces. 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]. CARE prices are 80 percent of standard prices at both tiers. In addition to giving us the household's correct pricing regime, we use CARE status to identify low-income households.

[6] 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].

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

III. Data

A. Natural gas billing data

The billing data in this paper come from two major utilities in California: Pacific Gas and Electric (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 (680,846 9-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 (610,207 9-digit zip codes) with a total of 2,526,503 households and 95,335,393 bills. Figure 7 depicts PG&E's and SoCalGas's coverage areas. Table 3 provides a brief summary of the billing data with regards to the numbers of bills, households, zip codes, and monetary values of the bills. Table 4 summarizes prices, quantities, and other variables of interest—pooling across all observations and also splitting the data by season or CARE status.

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 2 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. Because the billing data include most households' 9-digit zip codes, we are able to match households to other datasets—for instance, Census block-group data.

B. Weather data

Data on daily weather observations originate from the PRISM project at Oregon State University [PRISM Climate Group 2004]. We match this local, daily weather data to the household consumption data at the day by zip-code level. This dataset contains daily gridded maximum and minimum temperature for the continental United States at a grid cell resolution of roughly 2.5 miles. 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, which is based on the US Postal Service delivery routes for 2013. For small zip codes not identified by the shape file we have purchased the location of these zip codes from a private vendor[8]. We matched the PRISM grids to the zip code shapes and averaged the daily temperature data across the multiple grids within each zip code for each day. For zip codes identified as a point, we simply use the daily weather observation in the grid at that point. This results in a complete daily record of minimum and maximum temperature—as well as precipitation—at the zip-code level from 1980–2015.

IV. Empirical strategy

In this section we describe the empirical strategy we use to identify the price elasticity of demand for residential natural gas consumers. First, we present the basic estimating equation that drives 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.

A. Estimating equation

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

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

[8] zip-codes.com

where i and t index household and time; q denotes quantity demanded; and p denotes price.[9] The term $\lambda_{i,t}$ represent 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 by month-of-year fixed effects (*e.g.*, household #1 in January) and zip-code by month-of-sample fixed effects (*e.g.*, Fresno in January 2009; also called zip-code by year by month). A causally identified estimated of η yields the own-price elasticity of demand.

B. Challenges

Two main sources of endogeneity threaten identification in equation 1.

The first challenge in identifying this price elasticity of demand is the potential endogeneity that results from price and quantity being simultaneously determined by the equilibrium of supply and demand—*simultaneity* (*e.g.*, Woolridge 2009). 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 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 pricing within the Californian natural gas market. Put simply, in tiered pricing regimes, the marginal price is a (weakly increasing, monotone) 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 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 another 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

[9] We first consider the price that classical economic theory deems relevant: the current period's marginal price. We also provide results using other measures of price, *e.g.*, average price, average marginal price, and baseline (first-tier) price.

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.

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 utilize the simplest set of controls. The "identification strategy" present in Table 5 makes no attempt to correct for the aforementioned potential biases outside of a fairly rich set of fixed effects—a household by month-of-year fixed effect and a city by month-of-sample fixed effect. We also vary whether we control for heating degree days (HDDs) during the billing period. The rightmost columns for each price control for city by month-of-sample fixed effects.

The six regressions in Table 5 utilize two different measures of price: (1) the household's marginal price during a given bill, and (2) the household's baseline (first-tier) price during the given bill. These two—rather related—measures of price yield considerably different results—differing both quantitatively and qualitatively. The baseline price suggests an elasticity of approximately −0.10, while the marginal price indicates a *positive* demand elasticity of approximately 1.05. The substantial differences across estimates in Table 5 suggests 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 the *price-is-a-function-of-quantity* flavor of simultaneity 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 elasticity might appear to be reasonable in terms of magnitude, it is still not necessarily identified, as it still may suffer from simultaneity bias. Simply adding more observations in the flavor of the big data movement does not address this potential endogeneity.[10] The OLS results in Table 5 do not provide any of the obvious signs of the

[10]When we use this specification (with baseline price) in the full sample, we obtain estimates for the price

existence of the second type of simultaneity bias discussed above—classical simultaneity from price and quantity's simultaneous determination in a system's equilibrium. In the presence of such endogeneity, one might expect the inclusion of heating degree days or city by month-of-sample to alter the coefficients more than we observe in Table 5. However, this lack of considerable change in coefficients is not evidence of a lack of simultaneity. It is fundamentally a statistically untestable issue which stems from the theoretical setup of how market prices originate.

Finally, it is worth noting that the baseline-price based elasticity estimates are well within the range of estimates from the existing literature, as shown in Table 1. This outcome warrants some concern, as it suggests that some of these estimates may suffer from endogeneity.

C. Solutions

Having shown that OLS with fixed effects 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 combines a spatial discontinuity with an instrumental variables approach.

i. Discontinuities

A common route toward identification involves finding relatively small geographic units that receive different prices within the same time period. Arbitrary administrative boundaries that determine policies' catchment areas provide a popular tool in this context, *e.g.*, Dell; Chen et al.; Ito. 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 PG&E and SoCalGas bisects eleven cities—three clusters—in southern California. Figure 7 displays the two utilities' service areas (sufficiently covered in the datasets). Figure 9 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.

elasticity of −0.33, −0.32, and −0.78 (specification/order corresponding to the three baseline-price columns of Table 5).

This identification strategy rests upon the assumption that households on one side of the utilities' border provide a valid control group for the 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 should be valid Ito. 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-month fixed effects, which absorb mean differences across households in a given calendar month. Thus, for the border discontinuity to be invalid, households must sort in a way consistent with their elasticities, and the utilities' price series must differ significantly in their variances. Because the data contain considerable variation in prices for both utilities and the panel contains approximately six years of monthly bills, this sort of sorting bias seems unlikely. Figure 10 suggests the generating distributions for the utilities' prices are quite similar (the standard deviation of the price series are 0.0940 and 0.1053 for PG&E and SoCalGas, respectively).

Ito 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 which prevent us from completely adopting Ito's identification strategy: discontinuities within electricity utilities' seven-tier pricing regime. By law, the electricity utilities in Ito's study are not allowed to move the price of the first two tiers—they must recover changes in their costs by moving tiers three through seven. Thus, marginal prices in Ito's setting move differently depending upon a household's tier. Ito argues that the residual variation—combining the spatial discontinuity with this pricing discontinuity and geographic and temporal fixed effects—is plausibly exogenous from demand shocks. Because natural gas has only two tiers—and because the absolute difference between the two tiers has relatively low variation—we are unable to take advantage of price-tier based discontinuities. Therefore, in addition to this utility-border-based discontinuity, we adopt an additional strategy to overcome endogeneity.

ii. Instrumental variables

The second element of our estimation strategy for identifying the price elasticity of demand for natural gas involves a traditional solution to 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 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 weeks preceding the change in prices. We also interact the spot price with *utility* to allow the utilities to differentially incorporate 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). This instrument satisfies the requirement of having a strong first stage, as the utilities base their prices, in part, on market prices of natural gas—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. However, several factors suggest that the exclusion restriction is plausibly valid. First, 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. Second, we interact the spot price instrument with utility. This interaction, conditional on zip-code by month-of-sample fixed effects, implies that the identifying variation in our instruments comes from the difference across the ways the two utilities' incorporate monthly spot-price shocks into their pricing regimes. Third, 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. Finally, we 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 shocks affecting national. Thus, we argue that the exclusion restriction is plausibly valid for our spot-price instrument.

Spot price first stage Table 6 provides the first-stage estimates for the two-stage least squares equations

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

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

where $\text{HH}_{i,t}$ is a household by month-of-year fixed effect, $\text{Zip}_{i,t}$ is a zip-code by month-of-sample fixed effect, and SCG_i is an indicator for whether the household's retail utility is SoCalGas. Figure 10 gives visual first-stage evidence—illustrating the link between the two utilities' prices and the Henry Hub spot price and also demonstrating how the utilities differ in their response to the spot price.

Table 6 gives the first-stage results corresponding to equation 2. Specifically, the Henry Hub spot price shown in Table 6 is the average natural gas spot price at Henry Hub during the 7 days preceding the change in pricing. Table 6 displays the first-stage results for three different prices that may be relevant to households: marginal price, average price, and baseline price (using the log of each variable). Within each price, we vary whether the regression controls for the billing period's heating degree days (HDDs).

Both Figure 10 and Table 6 demonstrate that the spot-price based instruments are quite strong (the F statistics testing the joint significance of the instruments exceed 400). This significance is unsurprising, as the utilities purchase gas on the spot market and incorporate these costs directly into their price regimes. The significance of the interaction between spot price and utility (SoCalGas) in Table 6 implies the utilities differ appreciably in the ways that they incorporate spot-market costs into their pricing regimes—PG&E's pricing regime appears to be much less responsive to the spot price than SoCalGas.[11] Though the city-year-month fixed effect should control for most local demand shocks, bills do not perfectly match months. The within-bill HDDs variable controls for any remaining weather-based demand shocks. The results in Table 6 are robust to including within-bill heating degree days (the even-numbered columns), which suggests that the instrument is exogenous to local-California 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 Table 6 suggest the instrument is strongest—in terms of first-stage significance—for baseline price, followed by average price then 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, marginal price, is the noisiest, which is consistent with marginal price having the small first-stage F statistic of three prices.

iii. Instrumented prices and simulated instruments

In the preceding sections, we discussed how our spot-price based instrument—used in conjunction with the spatial discontinuity in utilities' service areas—may overcome the bias resulting from the fact that quantity and price (our dependent and independent variables) result from a simultaneously determined equilibrium. We now discuss the aspect our identification strategy that deals with the *price-is-a-function-of-quantity* endogeneity present in multi-tiered pricing contexts.[12] 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

[11] 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.

[12] This endogeneity is present both in marginal price and in average price.

above: instrumenting a household's price with the our Henry Hub spot price interacted with utility. Because this instrument only varies at the billing-period by utility level, 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 before the household's consumption decision. Thus, if the spot price provides a valid instrument for 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 prices 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. Thus, in application, one could either replace marginal (or average) price with baseline price *or* instrument one of the endogenous prices with baseline price. However, baseline price fails to capture the higher price that a household faces once it exceeds its total monthly allowance.

Option 3: Simulated instrument Simulated instruments provide a third option for breaking the *price-is-a-function-of-quantity* flavor of endogeneity. The simulated-instrument approach follows a methodology suggested by Ito. 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 (1) 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 the equation 4 slightly. First, we use the households' lagged consumption levels (from lagged bills 10 through 14 months prior) to determine in how many of the lagged periods would exceed this billing period's baseline allowance, *i.e.*,

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

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

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

Summarizing equations 5 and 6: this simulated instrument predicts that a household will exceed its allowance when the household exceeded its allowance in the majority of past bills (based upon lagged months 10 through 14).[13]

Table 7 provides the first-stage results consistent with equation 2 but with the simulated instrument of marginal price substituted for actual marginal price (we still instrument with the Henry Hub spot price).[14] The first-stage is again quite strong in this specification, and the results are qualitatively similar to the results in Table 6. Henceforth we will refer to the simulated instrument for marginal price as *simulated marginal price*.

For the sake of simplicity, all subsequent results utilize both the spatial discontinuity and the spot-price based instrument. To incorporate the three competing strategies discussed immediately above, we provide results consistent with the strategies: instrumenting with spot price, utilizing baseline price, and utilizing *simulated* marginal price (the the simulated instrument for marginal price). We now turn to our main results.

V. Results

In this section, we discuss the estimated price elasticities, using the empirical strategies extensively discussed above. After presenting the main results for the *pooled* elasticity (no

[13]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 (keeping the first stage strong), while allowing some distance from the current period (the exclusion restriction: preventing medium-run shocks from affecting both periods).

[14]It is worth noting that in this paper, any result utilizing 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.

heterogeneity), we further examine whether households' price responses (*i.e.*, elasticities) vary by season and/or by income.

A. Pooled price elasticity of demand for natural gas

Table 9 displays the results from the second-stage regression in equation 3. These results instrument log price with the Henry Hub spot price, exploit the spatial discontinuity at the zip-code level, and use the log of daily average consumption (in therms) as the outcome. Odd-numbered columns do not include heating degree days (HDDs); even numbered-columns include HDDs. Columns (1) and (2) estimate the elasticity using the log of marginal price, while columns (3) and (4) use the log of average price. Columns (5) and (6) use the log of baseline price. The estimates are robust to including HDDs or varying the type of price. This robustness to type of price also demonstrates robustness to how we control for the *price-is-a-function-of-quantity* endogeneity discussed above. The estimates for the price elasticity of demand range from −0.19 to −0.29.

Table 10 extends the results in Table 9 by adding *average marginal* price[15] and *simulated* marginal price. Each estimate in Table 10 controls for within-bill heating degree days. Table 10 displays further robustness to the choice of price. In Tables 9 and 10, the estimated price elasticity of demand for natural gas ranges from −0.19 to −0.29. Compared to their OLS-based counterparts in in Table 5, the marginal-price based estimates for the elasticity of demand now have opposite–and theoretically correct—signs. The magnitudes of the estimates of the elasticity are theoretically reasonable and within the range of previous findings. Furthermore, these estimates, are plausibly identified and utilize consumers' actual prices.

Tables 11–15 further examine the robustness of the elasticity estimates. Each table examines the robustness of the elasticity estimates for a given type of price—marginal price (Table 11), *simulated* marginal price (Table 12), average marginal price (Table 13), average price (Table 14), and baseline (first-tier) price (Table 15). Each table provides estimates with heating degree days (even-numbered columns) and without heating degree days (odd-numbered columns). In addition, each table provides estimates for in which we enforce

[15]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.

the spatial discontinuity at the city level—columns (1) and (2)—and at the zip-code level—columns (3) and (4). The elasticity estimates again display robustness to specification and type of price. Across the 20 specifications—four specifications for each of the types of price—the point estimates range from −0.17 to −0.29.

B. Heterogeneity

We now examine the evidence that the price elasticity of demand for natural gas varies across income levels and/or seasons. 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 or income groups. However, because OLS weights heterogeneous treatment effects by their share 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.[16] 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).[17]

[16]Because we do not have identifying variation in income level (or season), the heterogeneities that we estimate should be taken as descriptive statistics for the given group, rather than causal estimates. 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. 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.

[17]This definition reflects southern California's two seasons: warm and slightly less warm.

i. 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. Table 17 displays the second-stage results from these regressions, providing estimates of the elasticity of demand by income level (CARE status). We again vary whether we include heating degree days for robustness.

The results in Table 17 suggest that the results in the previous section may pool across heterogenous elasticities: we estimate the price elasticity for CARE (lower-income) households is approximately twice that of non-CARE (higher-income) households. Specifically, we estimate an elasticity of approximately −0.27 (0.057) for CARE households and −0.14 (0.048) for non-CARE households. The pooled estimate corresponding to these results is −0.19 (0.043) (column (2) in Table 11)—fairly close to the midpoint between the CARE estimate than the non-CARE estimate. Table 17 provides an addition insight into heterogeneous consumption behaviors across income levels: the results suggest that an addition heating degree day increasing consumption more in non-CARE (higher-income) homes than in CARE (lower-income) homes.

ii. 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. Table 18 displays the second-stage results from these regressions, providing estimates of the elasticity of demand by season. We again vary the inclusion of HDDs for robustness.

The results in Table 18 indicate a stark and significant difference between price elasticities in summer and winter months. The estimated price elasticity of demand for natural gas in summer months is approximately −0.038 (0.034) and does not differ significantly from zero. The estimated elasticity for winter months is approximately −0.47 (0.11) and differs significantly from zero at the 1-percent level. The pooled elasticity estimate corresponding to these results is approximately −0.19 (0.043) (column (2) in Table 11). The results also suggest differences in the effect of a heating degree day across the seasons, with HDDs in winter months increasing consumption more than HDDs in summer months. Both sets of results provide strong evidence that households' consumption and price-response behaviors vary by season.

iii. 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—interacting the heterogeneity dimensions discussion above (income and season).

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. Table 18 displays the second-stage results from these regressions, providing estimates of the elasticity of demand by season and CARE status. All results in Table 19 include HDDs.

The results in Table 19 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 (CARE status). Specifically, the results in Table 19 indicate that both income groups are essentially inelastic to prices in summer months: we estimate a "summertime" price elasticity of −0.080 (0.041) for CARE households and −0.021 (0.041) for non-CARE households. In winter months, both sets of consumers are significantly more elastic, but CARE households are especially more elastic. We estimate the "wintertime" price elasticity of demand for natural gas is −0.61 (0.13) for CARE households and −0.34 (0.11) for non-CARE households. Again, the pooled elasticity corresponding to these results is approximately −0.19 (0.043) (column (2) in Table 11), which is a bit lower than the average of these four elasticities. The estimated effects of within-bill heating degree days in Table 19 also bear evidence of this two-way heterogeneity: the difference between responses to HDDs in summer and winter months appears to differ by income group. Overall, Table 19 demonstrates the potential for substantial and important heterogeneity underlying commonly estimated pooled elasticities.

VI. Conclusion

This paper combines millions of household natural gas bills with manifold identification strategies 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, in conjunction with a supply-shifting instrument that generates plausibly exogenous variation in price, the preferred specification results in an estimated elasticity of −0.26 [−0.38, −0.14]. This estimate is robust to specification choices which include within-bill weather, a number of different price instruments, and definition of price. In the twenty specification that we estimate, the point estimates for the own-price elasticity range from −0.29 to −0.17. 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].

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 not statistically different from, zero. The winter price elasticity is −0.47. This heterogeneity suggests that households are much more price sensitive during their high-consumption months—the winter. These high-consumption winter months also correspond to the time of year in which consumers use natural gas in it most salient form: heating. When we break down the price elasticity across users and seasons, we show that subsidized consumers display the largest price sensitivity during the winter (−0.61). Neither type of customer displays a significant price response in the summer. These results suggest that if suppliers want to pass through costs to consumers, summertime is best—both for efficiency and for progressivity.

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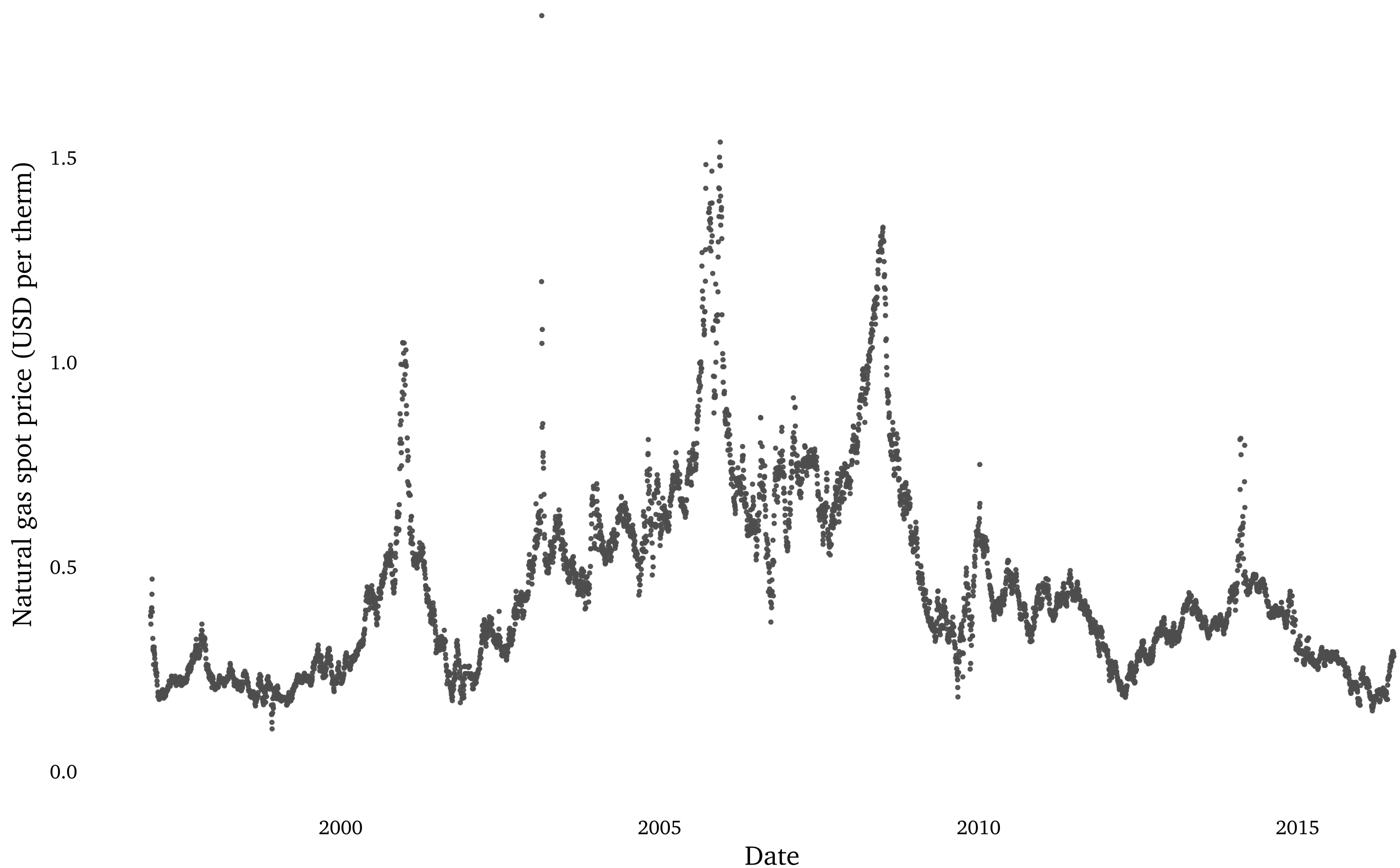
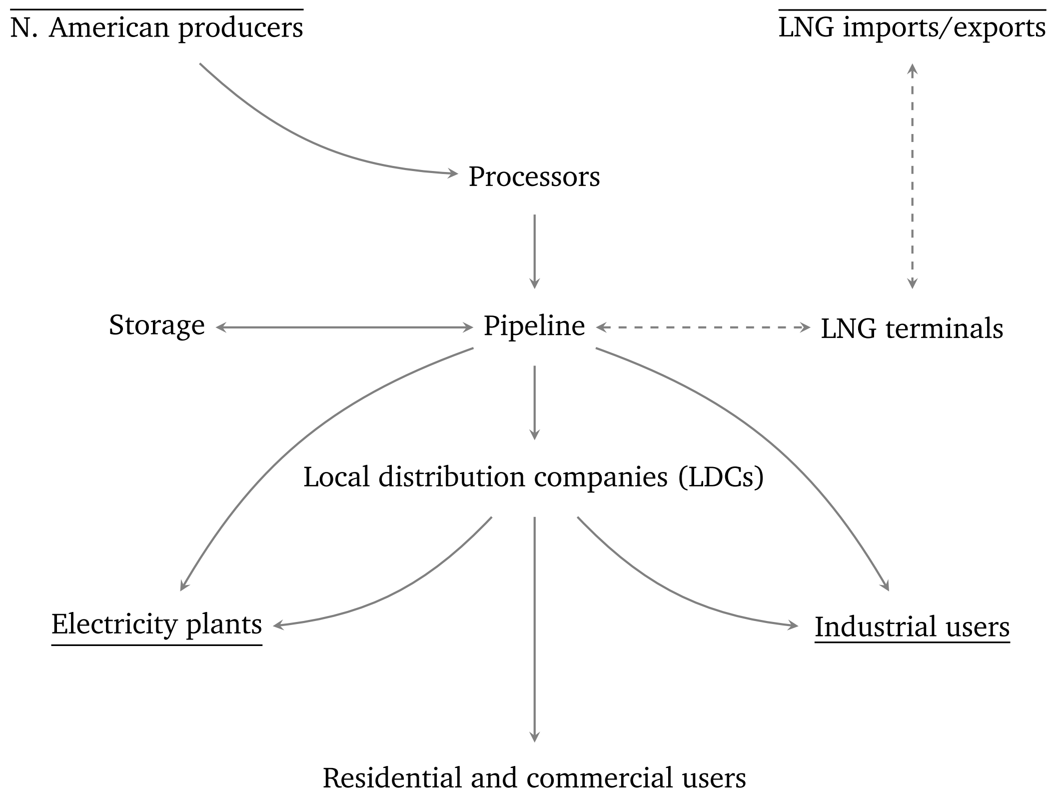
VII. Figures

Figure 1: **Henry Hub natural gas spot price,** 1997–2016



Source: U.S. Energy Information Administration

Figure 2: **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 off of Levine, Carpenter, and Thapa with slight modification following Brown and Yücel.

Figure 3: **Marginal *vs.* average price example:** PG&E, January 2009, climate zone 1

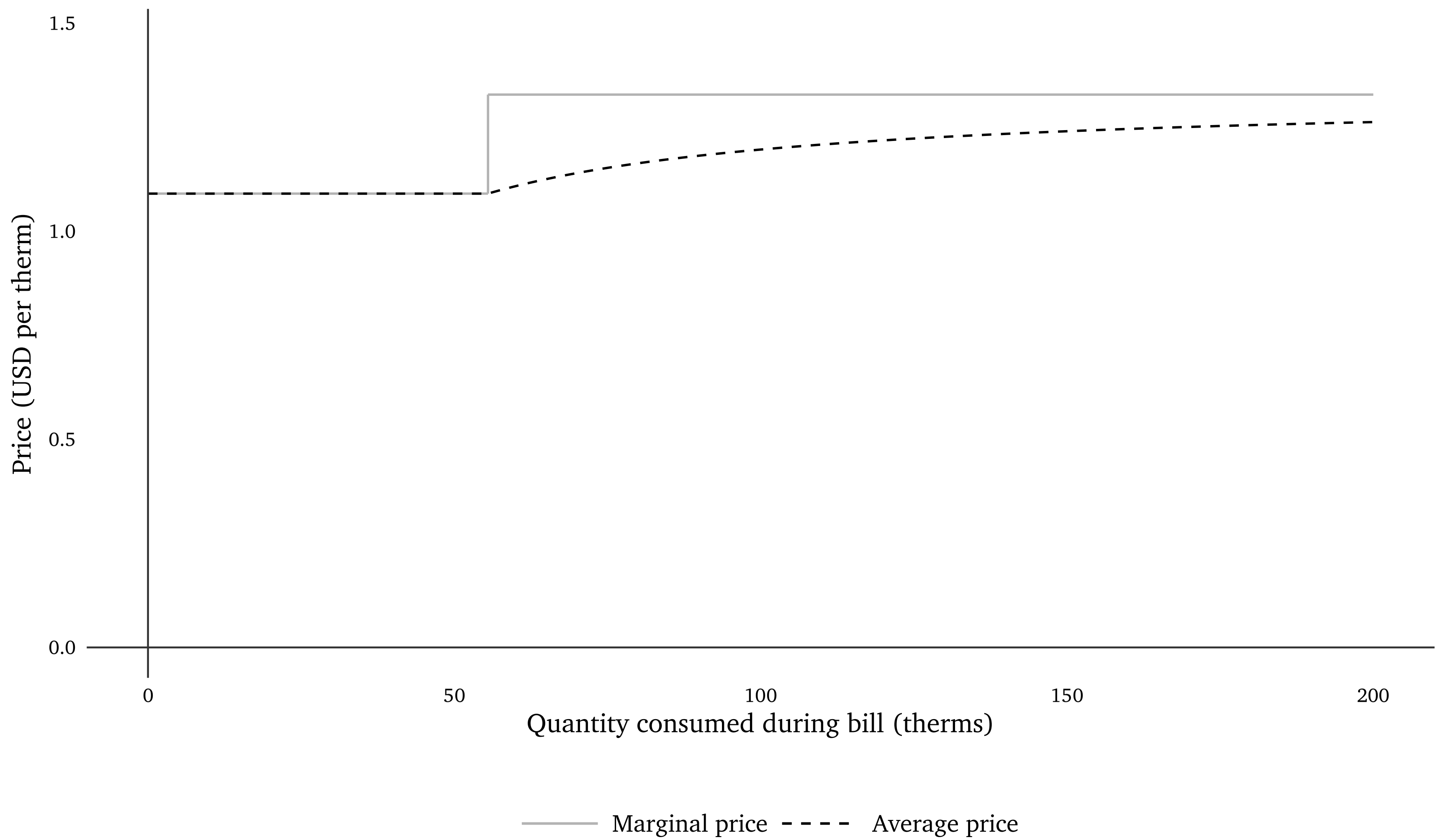


Figure 4: **Daily tier-one allowances over time:** PG&E (zone R) and SoCalGas (zone 1), 2009–2015

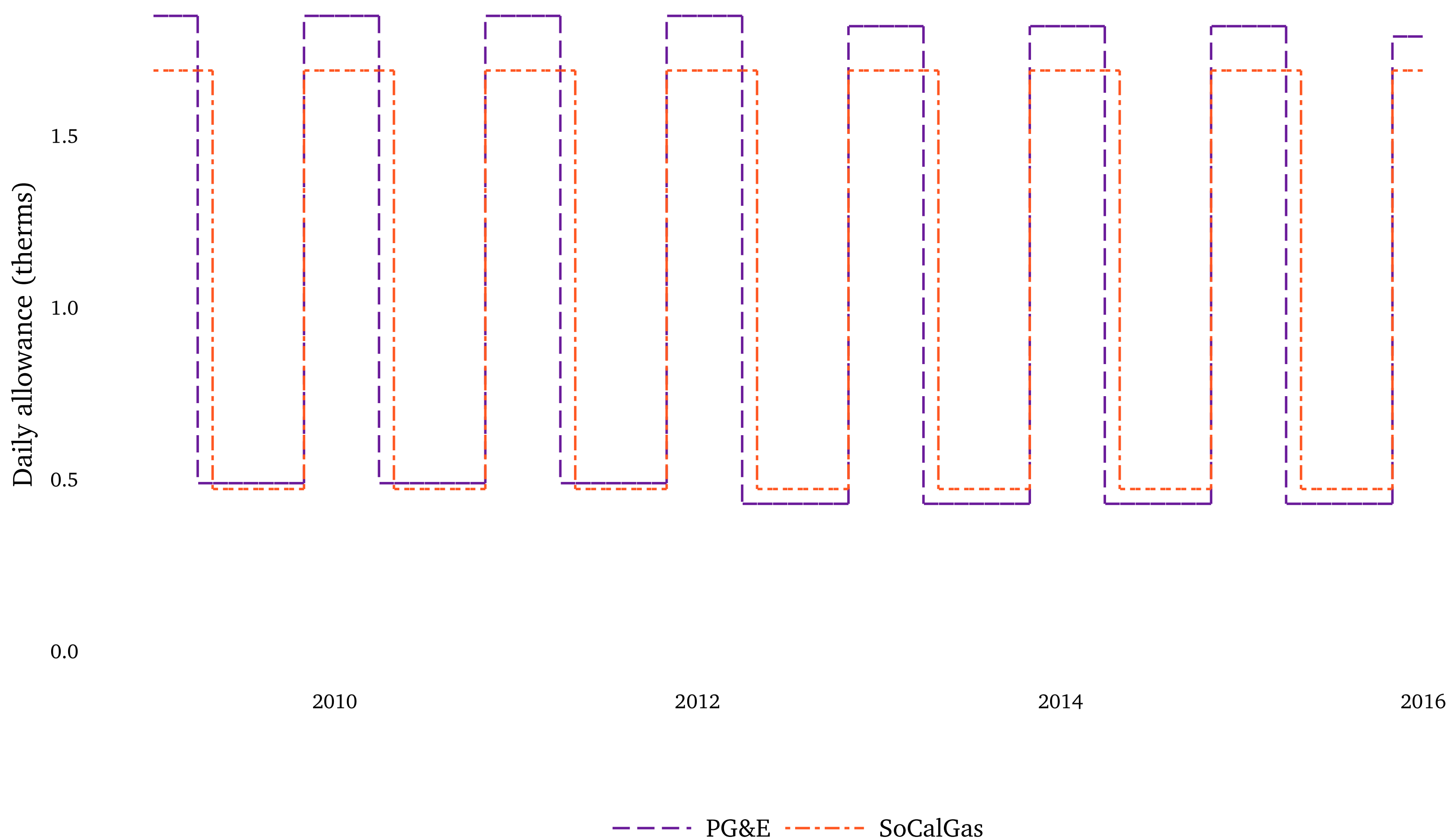


Figure 5: **Price regimes over time:** PG&E and SoCalGas, 2009–2015

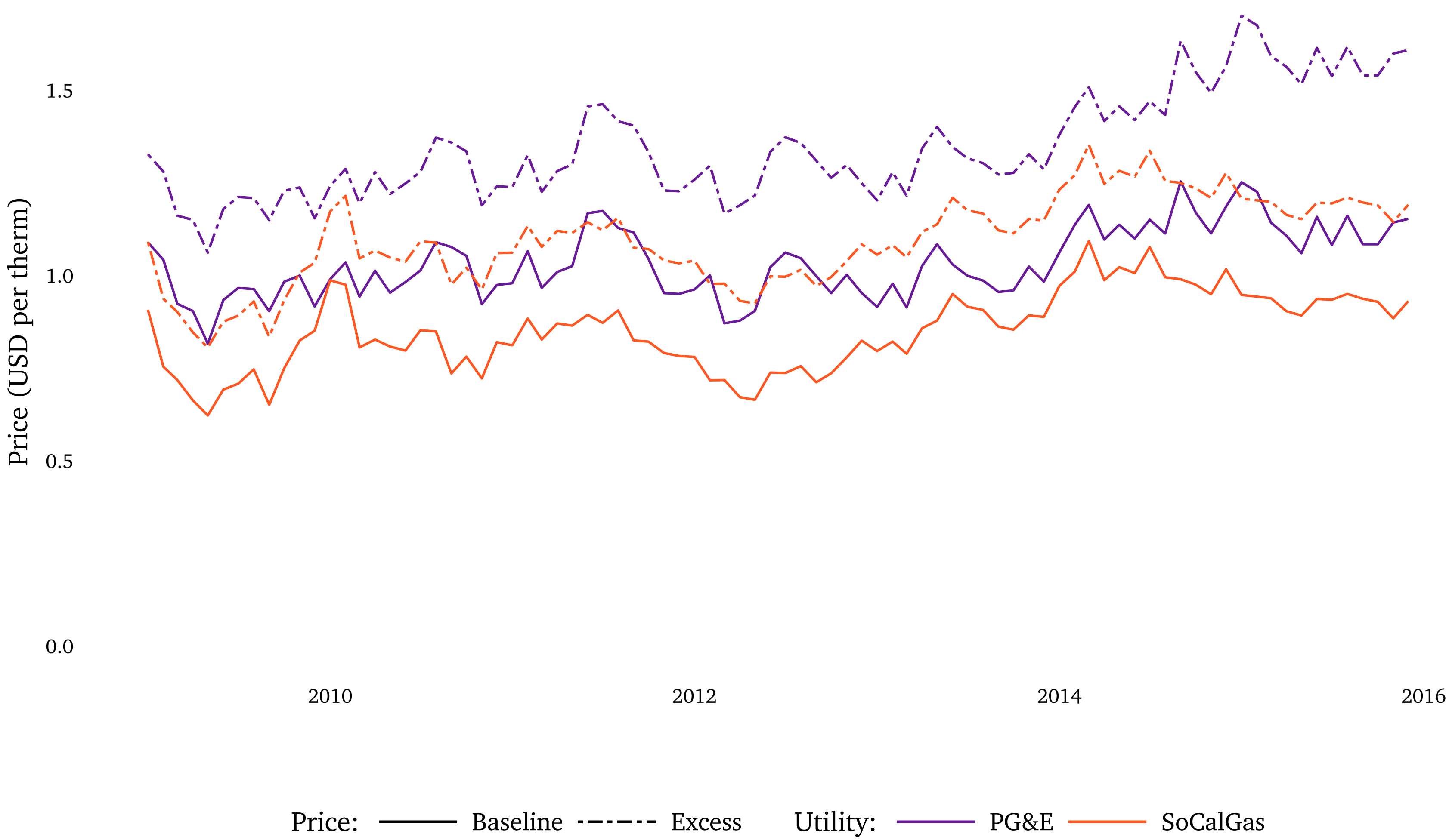


Figure 6: **California's 16 CEC climate zones:** determine daily allowance within season

Figure 7: **Natural gas service areas:** data coverage by zip code

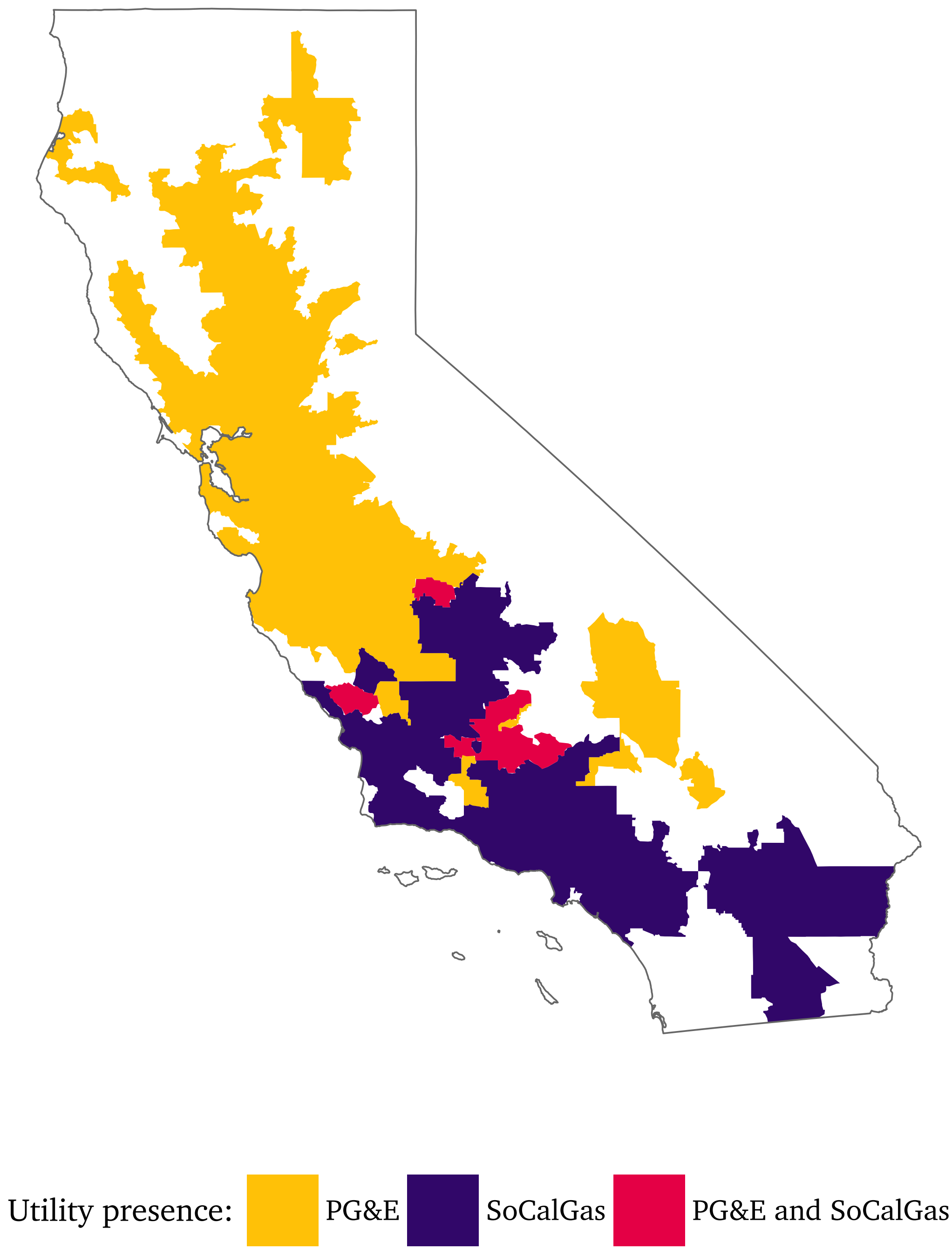
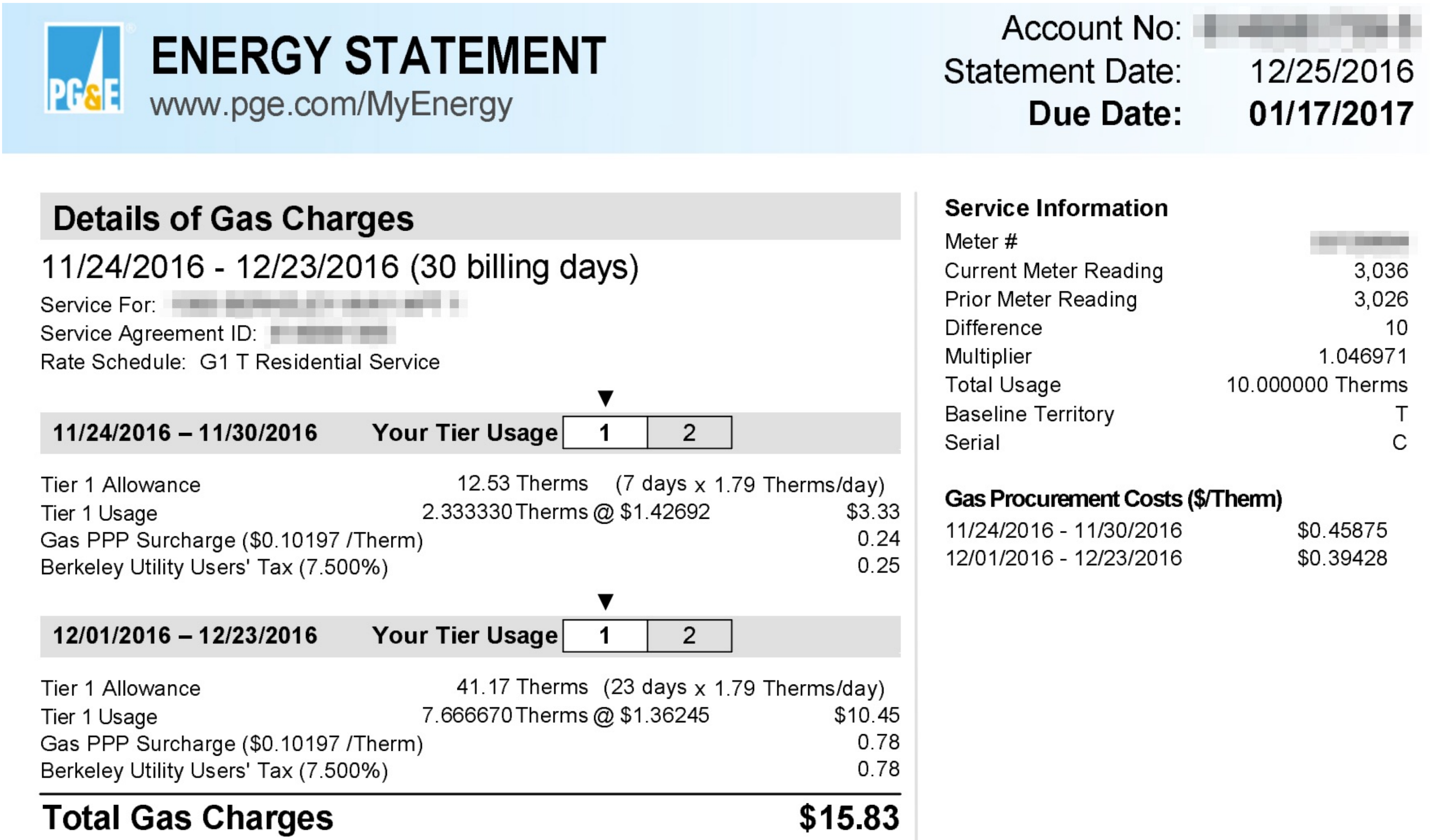


Figure 8: **Example bill:** PG&E residential natural gas bill



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

Figure 9: **Study-area discontinuity:** Cities served by both utilities

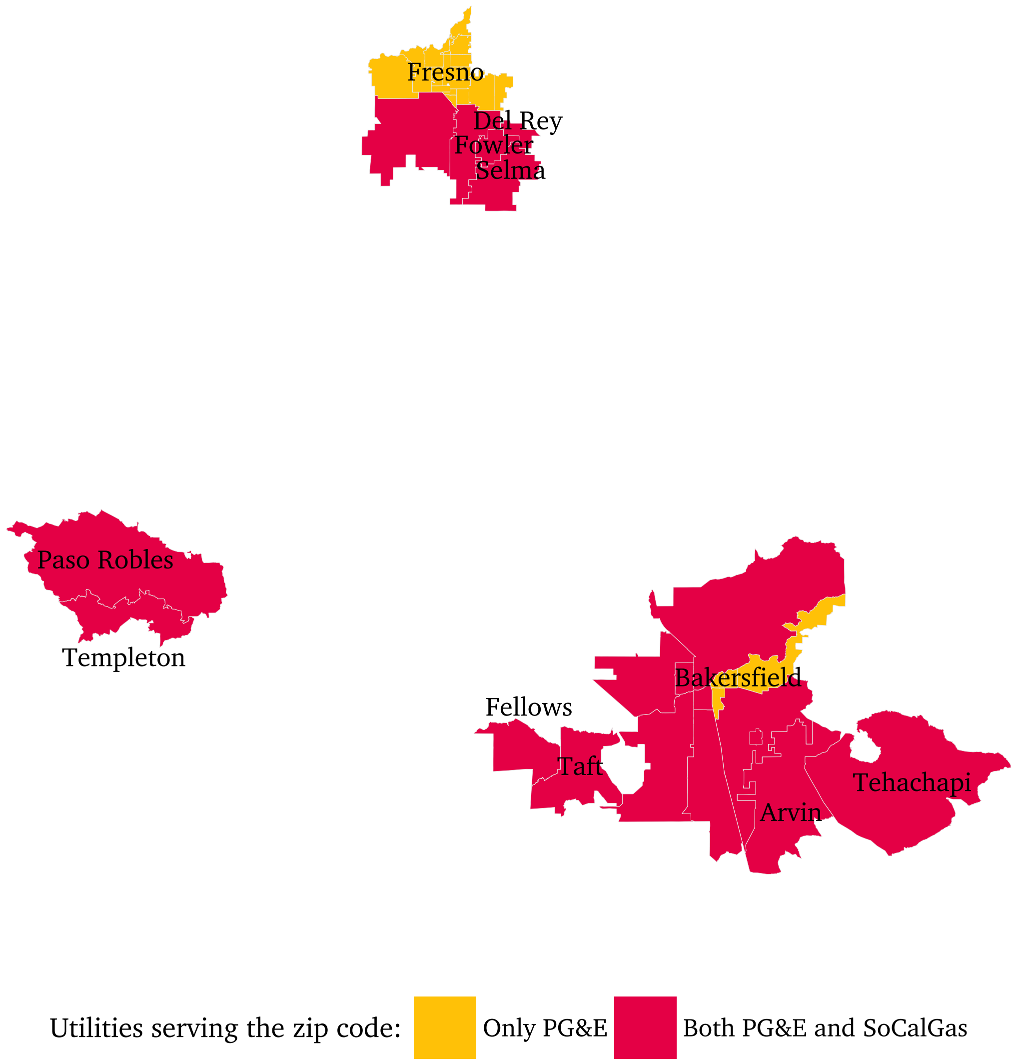
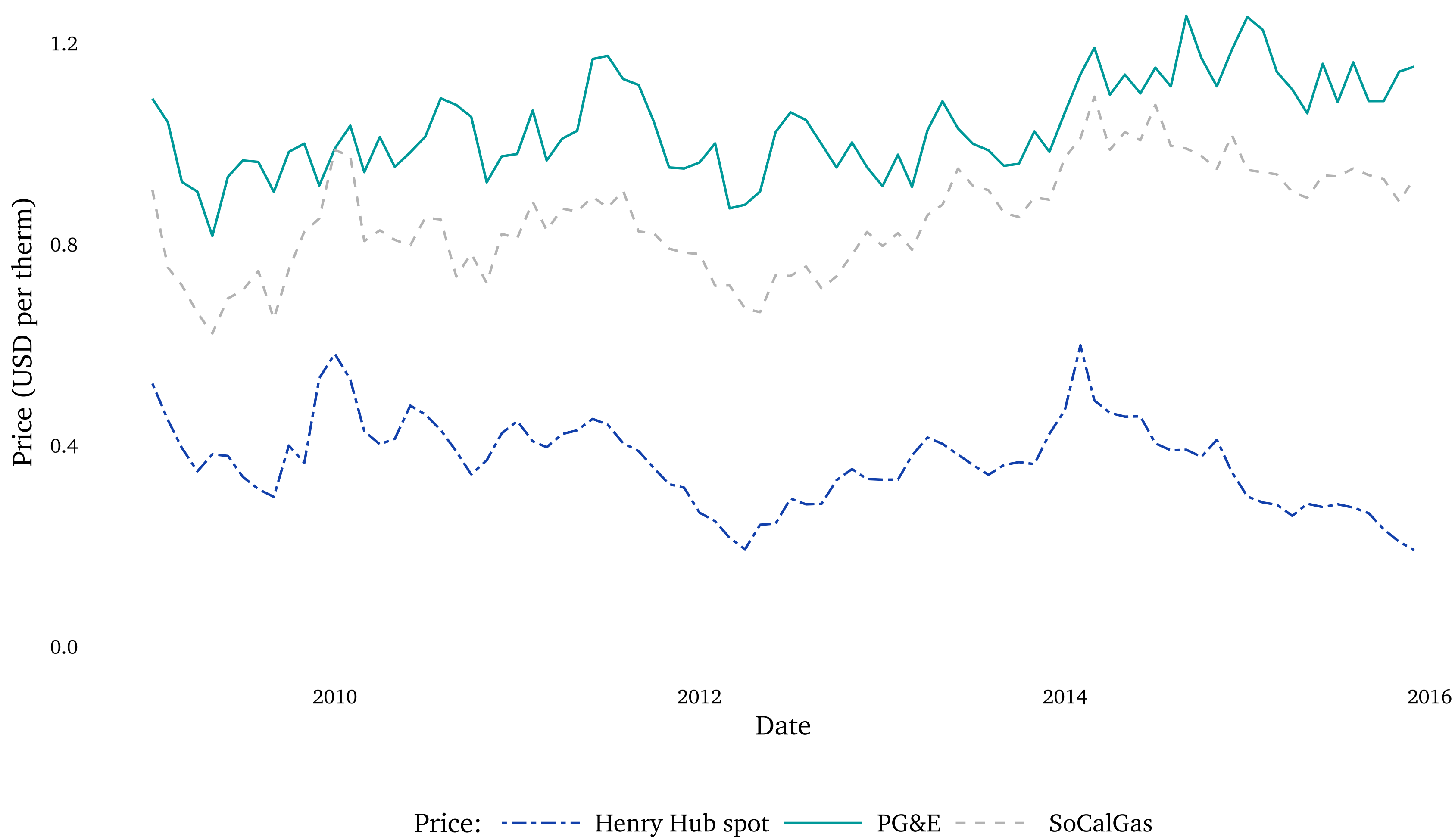


Figure 10: **Correlation across prices** Three relevant natural gas price series



VIII. Tables

Table 1: Prior point estimates of 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 (1999)	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

Adapted from Alberini et al. (2011)

Table 2: 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

Table 3: Billing data summaries

	PG&E	**SoCalGas**
N. 5-digit zip codes	597	611
N. 9-digit zip codes	680,846	610,207
N. unique households	5,888,276	2,526,503
N. bills	180,663,705	95,335,393
Approx. value (USD)	$5.71B	$3.28B

Table 4: Summaries of prices, quantities, and other variables of interest

		Split by season		**Split by CARE**	
Variable	**Overall**	Winter	Summer	CARE	Non-Care
Baseline price	0.9026	0.8836	0.9204	0.8080	0.9811
	[0.1419]	[0.1361]	[0.1448]	[0.0854]	[0.1311]
Excess price	1.1690	1.1477	1.1891	1.0445	1.2725
	[0.1742]	[0.1708]	[0.1751]	[0.1009]	[0.1534]
Average price	1.0211	1.0008	1.0402	0.9086	1.1147
	[0.1621]	[0.1583]	[0.1633]	[0.1004]	[0.1430]
Marginal price	1.0387	1.0121	1.0637	0.9338	1.1259
	[0.1983]	[0.1905]	[0.2021]	[0.1448]	[0.1944]
Therms	33.8273	50.9544	17.7311	33.1136	34.4204
	[30.7697]	[35.2487]	[11.5803]	[28.7629]	[32.3306]
Days	30.3994	30.5876	30.2225	30.4040	30.3955
	[1.3038]	[1.3843]	[1.1966]	[1.2761]	[1.3263]
Therms per day	1.1063	1.6588	0.5871	1.0840	1.1249
	[0.9936]	[1.1354]	[0.3838]	[0.9304]	[1.0429]
Total bill	34.9508	52.0750	18.8573	30.3135	38.8040
	[33.8812]	[39.8973]	[14.0069]	[27.2567]	[38.1017]
Within-bill HDDs	0.9398	1.7136	0.2126	0.9291	0.9488
	[0.8445]	[0.4219]	[0.3529]	[0.8443]	[0.8446]
(Percent) CARE	45.38%	45.00%	45.74%	100%	0%

Notes: Unbracketed values provide the means of the variables; bracketed values denote the variables' standard deviations. These statistics come from the 16,375,407 observations underlying the main specifications in this paper.

Table 5: OLS-based elasticity estimates

	Dependent variable: Log(Consumption, daily avg.)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Marginal price)	1.0162***	1.0483***	1.0862***			
	(0.0159)	(0.0103)	(0.0097)			
Log(Baseline price)				−0.103***	−0.0958***	−0.1097***
				(0.0132)	(0.0096)	(0.0098)
HH-month FE	T	T	T	T	T	T
Zip code's HDDs during bill	F	T	T	F	T	T
Year-month FE	T	T	F	T	T	F
City-year-month FE	F	F	T	F	F	T
N	16,375,407	16,375,407	16,375,407	16,375,407	16,375,407	16,375,407

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands. *Significance levels:* *10%, **5%, ***1%.

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

	Dependent variable					
	Log(Marginal price)		Log(Average price)		Log(Baseline price)	
	(1)	(2)	(3)	(4)	(5)	(6)
Spot price	0.2174*	0.2391**	0.3299***	0.3416***	0.5345***	0.5383***
	(0.1268)	(0.113)	(0.0956)	(0.089)	(0.0669)	(0.0653)
Spot price × SoCalGas	0.7835***	0.7816***	0.7217***	0.7207***	0.8361***	0.8358***
	(0.0275)	(0.0282)	(0.0236)	(0.0238)	(0.0232)	(0.0232)
F stat. for instruments	482.7	442.7	558.1	541.6	788.9	791.7
Bill's HDD	F	T	F	T	F	T
HH-month FE	T	T	T	T	T	T
Zip-year-month FE	T	T	T	T	T	T
N	16,375,407	16,375,407	16,375,407	16,375,407	16,375,407	16,375,407

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands. *Significance levels:* *10%, **5%, ***1%.

Table 7: **First-stage results**: Instrumenting *simulated* marginal price with HH spot price

	Dependent variable: Log(*Simulated* marginal price) (1)	(2)
Spot price	0.3828^{***}	0.4069^{***}
	(0.1193)	(0.1056)
Spot price $\times$ SoCalGas	0.8201^{***}	0.8178^{***}
	(0.0272)	(0.0275)
F stat. for instruments	548.2	525.1
Lags used for simulated instrument	10–14	10–14
Bill's HDD	F	T
HH-month FE	T	T
Zip-year-month FE	T	T
N	13,675,986	13,675,986

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands. *Significance levels:* *10%, **5%, ***1%.

Table 8: **First-stage results:** Instrumenting marginal price with *simulated* marginal price

	Dependent variable: Log(Marginal price)			
	(1)	(2)	(3)	(4)
Log(*Simulated* marginal price)	0.3300***	0.3263***	0.3142***	0.3105***
	(0.0045)	(0.0041)	(0.0049)	(0.0044)
Within-bill HDDs		−0.0389***		−0.0411***
		(0.005)		(0.0051)
Lags used for simulated instrument	10–14	10–14	11–13	11–13
HH-month FE	T	T	T	T
Zip code's HDDs during bill	F	T	F	T
Zip-year-month FE	T	T	T	T
N	13,675,986	13,675,986	13,412,664	13,412,664

Notes: By "*simulated* marginal price", we mean the simulated instrument for marginal price. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands.
As discussed in the Empirical strategy section, the numbers of observations vary based upon which numbers of lags we use in calculating the *simulated instrument* for marginal price.
Significance levels: *10%, **5%, ***1%.

Table 9: **Second-stage results**: Instrumenting consumers' prices with Henry Hub spot price

Dependent variable: Log(Consumption, daily avg.)

	Type of Price					
	Marginal price		Average price		Baseline price	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Price)	-0.1853^{**}	-0.2125^{***}	-0.2562^{***}	-0.2902^{***}	-0.2573^{***}	-0.2903^{***}
instrumented	(0.0803)	(0.0611)	(0.0943)	(0.0689)	(0.0874)	(0.0608)
Within-bill HDDs		0.3617^{***}		0.3651^{***}		0.3716^{***}
(thousands)		(0.0153)		(0.0152)		(0.0152)
F stat. for instruments	482.7	442.7	558.1	541.6	788.9	791.7
Bill's HDD	F	T	F	T	F	T
HH-month FE	T	T	T	T	T	T
Zip-year-month FE	T	T	T	T	T	T
N	16,375,407	16,375,407	16,375,407	16,375,407	16,375,407	16,375,407

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands. *Significance levels:* *10%, **5%, ***1%.

Table 10: **Second-stage results**: Instrumenting consumers' prices with Henry Hub spot price

Dependent variable: Log(Consumption, daily avg.)

	Type of Price				
	Mrg. (1)	Sim. Mrg. (2)	Avg. Mrg. (3)	Avg. (4)	Baseline (5)
Log(Price)	-0.2125^{***}	-0.2581^{***}	-0.2464^{***}	-0.2902^{***}	-0.2903^{***}
instrumented	(0.0611)	(0.0622)	(0.0563)	(0.0689)	(0.0608)
Within-bill HDDs	0.3617^{***}	0.3686^{***}	0.3596^{***}	0.3651^{***}	0.3716^{***}
(thousands)	(0.0153)	(0.0159)	(0.0149)	(0.0152)	(0.0152)
F stat. for instruments	442.7	525.1	722.6	541.6	791.7
Bill's HDD	T	T	T	T	T
HH-month FE	T	T	T	T	T
Zip-year-month FE	T	T	T	T	T
N	16,375,407	13,675,986	16,375,407	16,375,407	16,375,407

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands. By "*simulated* marginal price", we mean the simulated instrument for marginal price. As discussed in the Empirical strategy section, the numbers of observations vary based upon which numbers of lags we use in calculating the *simulated instrument* for marginal price.
Significance levels: *10%, **5%, ***1%.

Table 11: **Second-stage results**: Instrumenting marginal price with Henry Hub spot price

	Dependent variable: Log(Consumption, daily avg.)			
	(1)	(2)	(3)	(4)
Log(Marginal price)	-0.1742^{***}	-0.1887^{***}	-0.1853^{**}	-0.2125^{***}
instrumented	(0.0529)	(0.0431)	(0.0803)	(0.0611)
Within-bill HDDs		0.3281^{***}		0.3617^{***}
(thousands)		(0.0168)		(0.0153)
F stat. for instruments	878.2	834.8	482.7	442.7
HH-month FE	T	T	T	T
Zip code's HDDs during bill	F	T	F	T
City-year-month FE	T	T	F	F
Zip-year-month FE	F	F	T	T
N	16,375,407	16,375,407	16,375,407	16,375,407

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands.
Significance levels: *10%, **5%, ***1%.

Table 12: **Second-stage results**: Instrumenting *simulated* marginal price with HH spot price

	Dependent variable: Log(Consumption, daily avg.)			
	(1)	(2)	(3)	(4)
Log(*Simulated* marginal price)	-0.2056^{***}	-0.218^{***}	-0.2222^{***}	-0.2581^{***}
instrumented	(0.0543)	(0.0438)	(0.086)	(0.0622)
Within-bill HDDs		0.3328^{***}		0.3686^{***}
(thousands)		(0.0175)		(0.0159)
F stat. for instruments	967.6	934.3	548.2	525.1
HH-month FE	T	T	T	T
Zip code's HDDs during bill	F	T	F	T
City-year-month FE	T	T	F	F
Zip-year-month FE	F	F	T	T
N	13,675,986	13,675,986	13,675,986	13,675,986

Notes: By "*simulated* marginal price", we mean the simulated instrument for marginal price. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands.
As discussed in the Empirical strategy section, the numbers of observations vary based upon which numbers of lags we use in calculating the *simulated instrument* for marginal price.
Significance levels: *10%, **5%, ***1%.

Table 13: **Second-stage results**: Instrumenting avg. mrg. price with Henry Hub spot price

	Dependent variable: Log(Consumption, daily avg.)			
	(1)	(2)	(3)	(4)
Log(Avg. marginal price)	-0.1824^{***}	-0.1992^{***}	-0.2152^{***}	-0.2464^{***}
instrumented	(0.0487)	(0.0388)	(0.0775)	(0.0563)
Within-bill HDDs		0.3272^{***}		0.3596^{***}
(thousands)		(0.0161)		(0.0149)
F stat. for instruments	1,319.5	1,231.7	789.8	722.6
HH-month FE	T	T	T	T
Zip code's HDDs during bill	F	T	F	T
City-year-month FE	T	T	F	F
Zip-year-month FE	F	F	T	T
N	16,375,407	16,375,407	16,375,407	16,375,407

Notes: By *average marginal price*, we mean the quantity-weighted marginal price. *Average marginal* price differs from *average* price by excluding fixed charges. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands.
Significance levels: *10%, **5%, ***1%.

Table 14: **Second-stage results**: Instrumenting average price with Henry Hub spot price

	Dependent variable: Log(Consumption, daily avg.)			
	(1)	(2)	(3)	(4)
Log(Average price)	-0.2231^{***}	-0.2414^{***}	-0.2562^{***}	-0.2902^{***}
instrumented	(0.0603)	(0.0482)	(0.0943)	(0.0689)
Within-bill HDDs		0.3308^{***}		0.3651^{***}
(thousands)		(0.0169)		(0.0152)
F stat. for instruments	935.3	922.8	558.1	541.6
HH-month FE	T	T	T	T
Zip code's HDDs during bill	F	T	F	T
City-year-month FE	T	T	F	F
Zip-year-month FE	F	F	T	T
N	16,375,407	16,375,407	16,375,407	16,375,407

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands.
Significance levels: *10%, **5%, ***1%.

Table 15: **Second-stage results**: Instrumenting baseline price with Henry Hub spot price

	Dependent variable: Log(Consumption, daily avg.)			
	(1)	(2)	(3)	(4)
Log(Baseline price)	-0.2139^{***}	-0.2314^{***}	-0.2573^{***}	-0.2903^{***}
instrumented	(0.0544)	(0.0424)	(0.0874)	(0.0608)
Within-bill HDDs		0.3352^{***}		0.3716^{***}
(thousands)		(0.017)		(0.0152)
F stat. for instruments	1,259.8	1,266.5	788.9	791.7
HH-month FE	T	T	T	T
Zip code's HDDs during bill	F	T	F	T
City-year-month FE	T	T	F	F
Zip-year-month FE	F	F	T	T
N	16,375,407	16,375,407	16,375,407	16,375,407

Notes: *Baseline price* denotes a household's first-tier price. Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands.
Significance levels: *10%, **5%, ***1%.

Table 16: **Second-stage results**: Instrumenting consumers' prices with Henry Hub spot price (2-week lag)

Dependent variable: Log(Consumption, daily avg.)

	Type of Price				
	Mrg. (1)	Sim. Mrg. (2)	Avg. Mrg. (3)	Avg. (4)	Baseline (5)
Log(Price)	-0.1547^{**}	-0.1363^{**}	-0.1574^{***}	-0.1909^{***}	-0.1819^{***}
instrumented	(0.0615)	(0.0598)	(0.0547)	(0.0675)	(0.0596)
Within-bill HDDs	0.3651^{***}	0.3763^{***}	0.3649^{***}	0.3682^{***}	0.3725^{***}
(thousands)	(0.0156)	(0.0161)	(0.0153)	(0.0154)	(0.0153)
F stat. for instruments	511.6	458.1	764.2	634.1	860.6
Bill's HDD	T	T	T	T	T
HH-month FE	T	T	T	T	T
Zip-year-month FE	T	T	T	T	T
N	16,375,407	13,675,986	16,375,407	16,375,407	16,375,407

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands. By "*simulated* marginal price", we mean the simulated instrument for marginal price. As discussed in the Empirical strategy section, the numbers of observations vary based upon which numbers of lags we use in calculating the *simulated instrument* for marginal price.
Significance levels: *10%, **5%, ***1%.

Table 17: **Heterogeneity by CARE status**:
Second-stage results, instrumenting marginal price with Henry Hub spot price

Dependent variable: Log(Consumption, daily avg.)

	CARE status			
	CARE households		Non-CARE households	
	(1)	(2)	(3)	(4)
Log(Marginal price)	-0.2276^{***}	-0.2656^{***}	-0.1255^{**}	-0.1372^{***}
instrumented	(0.0716)	(0.0570)	(0.0585)	(0.0483)
Within-bill HDDs		0.3112^{***}		0.3493^{***}
(thousands)		(0.0173)		(0.0184)
F stat. for instruments	727.1	723.6	795.3	750.1
Zip code's HDDs during bill	F	T	F	T
HH-month FE	T	T	T	T
City-year-month FE	T	T	T	T
N	7,431,500	7,431,500	8,943,907	8,943,907

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands. CARE status 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]. CARE prices are 80 percent of standard prices at both tiers. Each column represents a separately estimated regression. *Significance levels:* *10%, **5%, ***1%.

Table 18: **Heterogeneity by season**:
Second-stage results, instrumenting marginal price with Henry Hub spot price

Dependent variable: Log(Consumption, daily avg.)	**Season**			
	Winter months		Summer months	
	(1)	(2)	(3)	(4)
Log(Marginal price)	-0.4153^{***}	-0.4736^{***}	-0.0384	-0.0382
instrumented	(0.1159)	(0.1064)	(0.0478)	(0.0336)
Within-bill HDDs		0.3201^{***}		0.2835^{***}
(thousands)		(0.0216)		(0.0157)
F stat. for instruments	265.1	252.3	922.1	929.6
Zip code's HDDs during bill	F	T	F	T
HH-month FE	T	T	T	T
City-year-month FE	T	T	T	T
N	7,933,660	7,933,660	8,441,747	8,441,747

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands. Each column represents a separately estimated regression. We define *winter* as October through March.
Significance levels: *10%, **5%, ***1%.

Table 19: **Heterogeneity by CARE status and season**:
Second-stage results, instrumenting marginal price with Henry Hub spot price

Dependent variable: Log(Consumption, daily avg.)

	Season and CARE status			
	(1) Summer CARE	(2) Summer Non-CARE	(3) Winter CARE	(4) Winter Non-CARE
Log(Marginal price)	-0.0797^{*}	-0.0208	-0.6062^{***}	-0.3402^{***}
instrumented	(0.0407)	(0.0412)	(0.1343)	(0.1133)
Within-bill HDDs	0.2652^{***}	0.3014^{***}	0.2927^{***}	0.3519^{***}
(thousands)	(0.0195)	(0.0165)	(0.0233)	(0.0235)
F stat. for instruments	737.5	787	196.4	248.8
Zip code's HDDs during bill	T	T	T	T
HH-month FE	T	T	T	T
City-year-month FE	T	T	T	T
N	3,861,459	4,580,288	3,570,041	4,363,619

Notes: Errors are two-way clustered within (1) household and (2) utility by climate-zone by billing-cycle. Heating degree days (HDDs) are in thousands. Each column represents a separately estimated regression. CARE status 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]. CARE prices are 80 percent of standard prices at both tiers. We define *winter* as October through March. *Significance levels:* *10%, **5%, ***1%.

A Appendix

A. 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 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 computers time-weighted average prices (and allowances)—aggregating the prices and allowances from the calendar months by the number of days the bill spent in each month.

B. Robustness to lags in instrument

Table 16 replicates Table 10 but alters the definition of the spot-price based instrument, replacing the 1-week lagged, weekly average of the Henry Hub spot price (shown in the main results) with the 2-week lagged, weekly average of spot price (shown in Table 16). The two tables provide qualitatively similar results. However, the two-week-lag based results provide consistently smaller point estimates for the price elasticities.

C. Data work

In this section, I describe the exclusion and cleaning choices that I made while preparing the data for analysis. My R script is 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 dropped bills missing any critical information: number of therms (quantity), revenue, *etc.* .
- We dropped **households** whose bills (revenue or quantity) were outside the central 99% of data (*i.e.*, in the bottom 0.5% or in the top 0.5%).
- 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.